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Laboratory and field trials of the ability of vegetated porous paving to remediate pollutants

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Abstract

Flooding is impossible to prevent completely, consequences of excess water can however, be reduced and often avoided via flood risk management. With the increase in impermeable surfaces, approaches that have the intention of imitating natural drainage to manage storm-water are known as Sustainable (Urban) Drainage Systems (SUDS). Pollutants from vehicles have been identified as a concern in the urban environment, with origins including exhaust emissions, engine oil leakage and erosion of vehicle components.

Investigation of vegetated parking surfaces (VPS) to limit the impact of pollutants are scarce, therefore this study aims to determine pollution tolerance of grass species for use in VPSs, prior to investigating the effects that vehicles have on a vegetated surfaces and alternative methods in which to analyse them.

A pot trial investigated effects of increasing oil concentrations on the growth of four grass species. *F. rubra* L. was found to tolerate contamination to a higher degree than the other species and *L. perenne* L. produced more cumulative biomass throughout the investigation. A parallel study determined that Ca, Cu, K, Mg, Mo, P and Zn accumulated in grass shoots, indicating that *F. rubra* L. and *L. perenne* L. may be suitable for further analysis.

A field trial focused on a regularly-used *L. perenne* L.-covered VPS at a local school, analysing the influence of vehicles on vegetated parking bays. Compaction and mean element concentrations increased across the VPS, with distance from the roadside. Use of mineral magnetism as a proxy for geochemical detection did not prove successful as no significant correlation was identified between magnetic susceptibility (χ) and element concentration.

Use of GIS provided this study with an alternative method for data presentation. Usually covering large scale analyses, an interactive geovisual map of geochemical dispersal and compaction across the VPS provided a novel method of visualising results from an investigation of this scale.

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Dedicated to Joel

Glossary

°C – degree Celsius

µg – micrograms

µm – micrometres

2D – Two Dimensional

3D – Three Dimensional

Al - Aluminium

ANOVA – Analysis of Variance

As – Arsenic

Ba – Barium

Bartington MS2 – Bartington Magnetic Susceptibility System

BMP – Best Management Practice

Ca - Calcium

Cd – Cadmium

Ce – Cerium

CIRIA – Construction Industry Research and Information Association

Co – Cobalt

Cr – Chromium

$CrPbO_4$ – Chromium Lead Oxide

Cs – Cesium

Cu – Copper

DC – District Council

DCR – Department of Conservation and Recreation

DEFRA – Department for Environment and Rural Affairs

DI – De-ionised water

DNA – Deoxyribonucleic acid

EA – Environment Agency

EC_{50} – Median Effective Concentration

ED_{50} – Effective Dose required for response effect in 50%

EDINA – Edinburgh Data and Information Access

EPA – Environmental Protection Agency

ERASMUS – European Scheme for Mobility of University Students

ESRI – Environmental Systems Research Institute

Eu – Europium

EU – European Union

Fe – Iron

FWMA – Flood Water Management Act

g – gram

g/cc – grams per cubic centimetres

g/m^2 – grams per square metre

GIS – Geographical Information Systems

GPS – Global Positioning System

hf – high frequency

Hg – Mercury

ICP-MS – Inductively Coupled Plasma Mass Spectrometry

INCHEM – International Programme on Chemical Safety

IQR – Inter Quartile Range

IRM – Isothermal Remanent Magnetism

K - Potassium

kg – kilogram

kg/m2 – kilogram per square metre

KMO – Kaiser-Meyer-Olkin measure

La – Lanthanum

lf – low frequency

LGA – Local Government Association

Li – Lithium

Ltd. – Limited

MAFF – Ministry of Agriculture, Forestry and Fisheries

Mg – Magnesium

mg/kg – milligrams per kilo

ml – millilitre

mm - millimetre

Mn – Manganese

Mo – Molybdenum

MOT Type 1 – Type of crushed concrete

Na - Sodium

NCDENR – North Carolina Department for Environment and Natural Resources

Nd – Neodymium

ng/g – nanograms per gram

NHBC – National House Building Council

NHO_3 – Nitric acid

Ni – Nickel

O_2 – Oxygen

OS – Ordinance Survey

P – Potassium

P value – Probability value

PAH – Polycyclic Aromatic Hydrocarbon

PAP – Particulate-Associated Pollution

PASW – Predictive Analytics Software

Pb – Lead

PCA – Principal Component Analysis

pdf – Portable Document File

PGE – Platinum Group Elements

ppm – parts per million

PPS – Permeable Paving System

PPS25 – Planning Policy Statement 25

Pt - Platinum

R^2 – Coefficient of Determination

Rb – Rubidium

REE – Rare Earth Elements

S – Sulphur

Sb – Antimony

Sc – Scandium

SCS– Source Control Systems (Cambs)

Se – Selenium

SEPA – Scottish Environment Protection Agency

SFRA – Strategic Flood Risk Assessment

SIRM – Saturate Isothermal Remanent Magnetism

SLOPE function – Excel function describing slope, steepness of a line

Sm – Samarium

Sn – Tin

SPSS – Statistical Package for Social Sciences

Sr – Strontium

STRI – Sports Turf Research Institute

SUDS – Sustainable (Urban) Drainage Systems

Tb – Terbium

Th – Thorium

Ti – Titanium

TIN – Triangular Irregular Networks

UK – United Kingdom

UWTC – Urban Water Technology Centre

V – Vanadium

VPS – Vegetative Parking Surface

W – Tungsten

w/v – weight volume

w/w – weight/weight

Y – Yttrium

Zn – Zinc

ZnO – Zinc Oxide

Zr – Zirconium

χ – magnetic susceptibility

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Chapter 1 Introduction

It is impossible to completely prevent flooding, but the impact of excess water can be avoided and reduced through flood risk management. Recent years have seen flooding become a more regular occurrence in the UK; notably between 2007 and 2009 when significant parts of the UK suffered extreme downpours and localised flooding events. Flood risk can be classified as two factors: the likelihood of a flood event happening (the probability of a flood happening in any year, expressed as a percentage) and the impact that would result following an event (Mid Sussex DC 2008). Occurring from a number of sources, flooding is either caused by natural environmental aspects or due to interference of natural processes by humans (for example, the addition of a concrete surface to replace vegetation (Charlesworth *et al.* 2003)). If human intervention does not take flood risk into account on developments, problems such as damage to buildings and the environment, interference to the local and/or wider community and further expenditure for insurances and repairs, not to mention the threat to health, will cause significant disruption and can even endanger life (Mid Sussex DC 2008). An approach which has the intention of imitating natural drainage in order to manage stormwater is sustainable drainage (SUDS) (Bray 2000).

SUDS not only prevent flooding but also recharge watercourses, maintaining the quality of water flowing through the system and enhancing the environment (Bray 2000; Wilson, Bray and Cooper 2004). Oil pollution has been acknowledged as a key concern from the urban environment; origins include drips from vehicles and diffuse pollution from road surfaces (Napier *et al*. 2008a). Long-term benefits of utilising the SUDS approach can include reduction in the volume of water from the source, reduction in run-off rate and reduction in pollutants and contamination (Wilson, Bray and Cooper 2004). The following sections give a brief overview of SUDS and the various devices used in stormwater management.

1.1 SUDS Philosophy, SUDS Triangle and the SUDS Treatment Train

Source control for the treatment of stormwater runoff from areas of impermeable surfaces has become extensively acknowledged by drainage engineers in the UK (Ellis *et al.* 2004). Unlike conventional drainage that quickly remove water from a location, SUDS are designed to mimic natural flows of water, to minimise the impact of flooding and pollution, to sustainably manage water from developments and to provide biodiversity and amenity (Sharma 2008; Charlesworth *et al.* 2003, 2010).

Figure 1 SUDS Triangle (Urban Water Technology Centre 2010)

There are many publications using the SUDS triangle concept (Stephenson 2005) so only a brief mention will be made here. The SUDS triangle (Figure 1) represents the equal consideration of water quality, water quantity and amenity/biodiversity when designing drainage systems sustainably (Stephenson 2005; Scottish Executive Environmental Group 2007; SEPA 2010; UWTC 2010), whereas conventional drainage aims to remove as great a volume of water away from the source as possible, with little consideration for quality and amenity. Directing the water elsewhere, localised flooding may be prevented but this usually concentrates the problem elsewhere, resulting in severe flooding (Barrett 2005). Runoff can be routed through different interconnecting SUDS to receiving watercourses, (CIRIA 2005; SEPA 2010), which is referred to as the SUDS Treatment or Management Train. The treatments aim to change the flow and improve water quality in four stages, as shown in Figure 2. Runoff may not pass through all phases of the treatment train, depending on its source, but under ideal circumstances, runoff is dealt with locally and returned to the natural drainage system quickly and as close to the source as possible (CIRIA 2005).

1.2 Wastewater and stormwater

SUDS are capable of dealing with both stormwater and wastewater, both of which need to be considered when planning a development. Wastewater is what remains of the water supplied to maintain life and a standard of living, both residentially and industrially (Butler and Davies 2004). It results from domestic and sanitation activities, including showering and bathing water, laundry and dish washing (Environment Agency 2007). Pollutants in industrial wastewater are removed before discharge, including asbestos, lead, mercury, nitrates, phosphates, sulphur, oils and petrochemicals (Water Pollution Guide 2011).

Figure 2 The SUDS Treatment Train (CIRIA 2005)

By disrupting biochemical processes, these pollutants have been shown to harm roadside vegetation, wildlife, nearby human communities, posing threats to animals, plants and human health (Akbar *et al.* 2006). Once spent, wastewater must be disposed of appropriately to avoid contamination of groundwater and to prevent pollution and health risks (Burian and Edwards 2002). There are more occasions now where treated wastewater from cities is being used for irrigation purposes, which reduces the volume of wastewater discharges to waterways (Ochs and Plusquellec 2003).

Stormwater is so-called as it originates from precipitation that has fallen on urban areas (Butler and Davies 2004) and is the run-off that drains away (Burian and Edwards 2002). This requires disposal at source to prevent localised flooding; it can also contain toxins such as heavy metals, oil, pollutants and hydrocarbons from industry and the environment (Newman *et al.* 2004). SUDS aim to deal with contaminants in stormwater by controlling the rate of runoff and the quality of its composition; they can be installed in urban developments where the first flush of water through the drainage system can be highly polluting and present a hazard to environmental quality (Environment Agency UK 2007).

As stated earlier in this section, SUDS can deal with both wastewater and stormwater. Recent EU legislation pertinent to both wastewater and stormwater has been brought in due to water shortages and the deterioration in quality of receiving water bodies (Bixio *et al*. 2005). This has led to stringent urban wastewater treatment requirements being implemented by the EU through its adoption on 21 May 1991 of the Council Directive 91/271/EEC (European Commission 2013). The purpose of this legislation included wastewater discharge from domestic and residential premises, contaminated rainwater runoff and industrial wastewater discharge (DEFRA 2012). Key elements included:

- Preventing damage to the environment through the discharge of urban wastewater and wastewater from industry,
- The collection of urban wastewater and installation of treatment systems in built-up areas (in staged deadlines of 1998, 2000, 2005 or 2015, dependent on size and designated location), and
- Dependent on the sensitivity of the receiving waters, there are four levels of treatment: preliminary, primary, secondary and tertiary.

(van Riesen 2004; DEFRA 2012)

In terms of the legislation specific to rain- or stormwater, The Water Framework Directive 2000/60/EC came into effect at the end of 2000. Its focus was to design, improve and integrate methods of water resource management throughout Europe (Defrain 2010; DEFRA 2012), which sought to establish a framework for the protection of inland surface waters, coastal waters, groundwater and transitional waters (Defrain 2010).

These pieces of legislation focus on contaminants associated with processes occurring in the urban environment. The following section, therefore, reviews some of the contaminants and their environmental impacts.

1.3 Water pollutants

Runoff from surfaces, especially impervious areas and locations close to industrial locations and highways, is likely to be contaminated with various pollutants. Vehicle emissions and increased industrial activities have added to particulate-associated pollution (PAPs) (Readman, Mantoura and Rhead 1987; Hoffman, Knab and Appel 1999; Canbay 2010) and provide sources of inorganic (e.g. heavy metals) and organic (e.g. Polycyclic aromatic hydrocarbons (PAHs)) contaminants, which lead to degrading air and soil qualities in roadside environments (Lygren *et al.* 1984; Münch 1990; Unger and Prinz 1992), especially in the upper 2 cm layer of the surface (Dearing 1994). Organic and inorganic pollutants accumulate in topsoil, resulting in migration to groundwater or uptake in plants and microorganisms (Hoffman, Knab and Appel 1999).

Pollutants associated with the combustion of fuels, the wear of tyres and brake pads, rusting of vehicle components, and metals from catalysts are all likely sources of pollution at the roadside (Pihl and Raaberg 2000; Ozaki, Watanabe and Kuno 2004; Leitão 2005). Heavy metals are naturally occurring substances that are usually found in low concentrations in the environment (Martin and Griswold 2009) but those that have been identified as being associated with vehicular transport are included in Table 1:

Table 1. Heavy metals identified with vehicular transport

Author(s)	**Heavy metals**
Townsend 1998	Ba, Cr, Cu, Ni, Pb and Zn
Pihl and Raaberg 2000	Cd, Cr, Cu, Ni, Pb and Zn
Nouri and Naghipour 2002	Cd, Cu, Ni, Pb and Zn
Ozaki, Watanabe and Kuno 2004	As, Cd, Cu, Hg, Ni, Pb, Sb and Zn
Leitão 2005	Cd, Cr, Cu, Fe, Hg, Ni, Pb and Zn
Canbay 2010; Canbay, Aydin and Kurtulus 2010	Cd, Co, Cu, Ni, Pb and Zn

Alkali earth metals (Ca, Mg) have also been identified in leachate from reclaimed asphalt pavement (Townsend 1998), plus the alkali metal Na, as a consequence of de-icing salts in winter (Pihl and Raaberg 2000). PAHs are groups of chemicals produced from petrol and diesel combustion in vehicles (Takada, Onda and Ogura 1990; Townsend 1998; Nouri and Naghipour 2002), with particulate-associated pollutants (PAPs) resulting from exhaust emissions and fumes (Lercher, Schmitzberger and Kofler 1995). These heavy metals, PAHs and PAPs are hazardous to health and need removing before the runoff can migrate to receiving watercourses or groundwaters and cause contamination. SUDS have been shown to deal with contamination and current legislation has been drafted to encourage its use. The following section gives an overview of the way in which sustainable drainage legislation has been incorporated in urban planning of new homes and industrial development in the UK.

1.4 Sustainable Drainage Legislations

As stated in Section 1.1, flooding is natural and cannot always be prevented but serious impacts can be addressed through planning and management. In the UK, the floods of 2007-2009 have highlighted the need for more effective urban planning around flood plains and the Flood and Water Management Act (DEFRA 2010) passed by the government aims to implement this. The Act (DEFRA 2010), however, emphasises implementation of sustainable drainage in new builds and developments. Specific retrofit guidance prepared by CIRIA, aimed to resolve policy barriers and demonstrated SUDS technologies in existing developments (Timlett and Gordon-Walker 2010).

If climate change means prolonged intense rainfall events are to occur on a more regular basis (Timlett and Gordon-Walker 2010), the additional surface water is going to place an extra burden on the storm sewerage infrastructure, which will inevitably lead to further flooding (NHBC 2010). The EA highlighted that some housing developments had an influence on flood risk; 72% had insufficient sewerage capacity and 62% had breached water quality standards, putting additional strain on the infrastructure (NHBC 2010). By installing SUDS in situations such as this, runoff will be alleviated by redirecting excess water to either infiltration systems or to watercourses and by dealing with water quality issues caused by surface run-off and sewer overflows through a SUDS Treatment Train.

Developers that design and construct new housing and industrial developments, regional bodies and local planning authorities must complete and follow policy guidelines in the Strategic Flood Risk Assessments (SFRAs) from Planning Policy Statement 25 (PPS25) that are set by the Government. Policy guidelines ensure flood risks have been considered by assisting and encouraging sustainable developments and therefore preventing inappropriate constructions (PPS25 2006). If the incorporation of SUDS into a site during its development is not achievable, (for example facilities at source or site control as in Fig. 2) it is sometimes possible for the developers to investigate whether SUDS can be used to integrate a number of sites that are in close proximity to each other. Then the developer must contribute to implementation and management costs of off-site SUDS to deal with the on-site demand (Woking Borough Council 2004).

The Future Water Report (DEFRA 2008), UK Government's water strategy report highlights the vital role of water in health, life and well-being. Including minimum water efficiency standards for new build homes, long term plans for water demand management, reduction in wasting water and improving the management of surface water to prevent flooding to name a few, Future Water (2008) identifies that the Government cannot tackle these issues in its own. The public, water industries, land managers and local authorities must all work in unison to prevent water quality and quantity issues in the first place. Future Water (2008) has five main aims for water policy and management to achieve by 2030. Those that relate to the use of SUDS include the improvement of water quality for the environment and ecology, sustainably managing risks from flooding and erosion at the coast (including efficient stormwater management) and the sustainable use of water resource. By maintaining a sustainable balance between water supply, demand and behaviour, and making every effort to achieve lower levels of water consumption and wastage, the risks to water supplies, water environments and conservation sites will not be as severe as the consequences of using water as if it was an unlimited resource (Future Water 2008).

The Flood and Water Management Act 2010 addresses the risks of flooding and of coastal erosion (DEFRA 2010). Defining 'flood' as anywhere that is not normally covered in water, this Act considers floods to be caused by heavy rainfall, rivers/dams overflowing or being breached, tidal waters, groundwater or any other factors that do not include sewers and burst water mains pipes (DEFRA 2010). Aiming to enhance flood risk management and the methods in which water resources are managed, the Act clarifies roles and responsibilities and highlights a more risk-based approach to flood management (LGA 2010). DEFRA (2010) highlights several key features of the Act, including the encouragement of councils to use SUDS and to manage the risks of local floods. The full Flood and Water Management Act 2010 covers strategies that provide advice on risk management at national and local scales, covering areas such as funding, responsible authority, the amendment of other risk management acts. One strategy the Act suggests is Sustainable Drainage (DEFRA 2010); the following section therefore provides a brief description of SUDS and the way in which it provides flooding resilience as well as water quality improvements.

1.5 Sustainable Drainage Systems (SUDS)

Sustainable drainage is a concept that considers long term environmental and social factors in decisions regarding drainage. SUDS are designed using the same hydrological and hydraulic principles as conventional drainage (CIRIA 2005). The volume of runoff previously dictated the diameter of pipes, allowing efficient drainage into the storm sewerage infrastructure (Burian and Edwards 2002). The increase in impermeable surfaces and pollution risk from developments encouraged (Flintshire County Council 2007) the installation of SUDS so that hydrological issues were maintained, including considerations for pollution control and amenity.

There are several types of SUDS devices that are utilised in the UK. These include: green roofs and walls (Bass 2007), swale systems, balancing ponds and wetlands, soakaways and permeable paving (Butler and Davies 2004; Puehmeier *et al.* 2004; CIRIA 2005). Each SUDS device must be suitable for the area and the application it has been put there for; these are described briefly in the following sections.

1.5.1 Swale systems and filter strips

Figure 3 Swale (Thomas Engineering 2009)

Swale systems and filter strips are areas of vegetative landscape that possess a smooth surface and a downhill gradient for excess water to flow away from the impermeable location (Figure 4). As these SUDS are vegetated, they also act as contaminant filters and remove heavy metal elements, oil, dust and organic matter from surface-water (Cheltenham Borough Council 2003). Usual locations for swales and filter strips are at the side of roads and motorways, where run-off from the impermeable surface is likely to be contaminated with pollutants from vehicles (Haygarth and Jones 1992)

1.5.2 Balancing ponds and detention basin wetlands

Balancing ponds and detention basin wetlands are both types of wetland that designed to hold water when it rains (Figure 5). The way to distinguish which SUDS is a pond and which is a detention basin is that a pond contains water all of the time and holds more water during wet weather, whereas a detention basin is dry and free from water until a rainfall event (Woking Borough Council 2004).

Figure 4 Pond (Facey 2008)

Balancing ponds and detention basins slow run-off sufficiently for sediment to settle, allowing plants (i.e. reeds) to treat the pollutants (Development Control Technical Specialists 2006).

1.5.3 Soakaways and infiltration devices

Soakaways and infiltration devices are surface or below-ground structures that are designed to drain water away from the surface and straight into the ground (Figure 6). They deal with the excess surface water from the source and run-off is often directed to an infiltration device, such as a swale (Woking Borough Council 2004).

Figure 5 Soakaway (Environmental Management Solutions Ltd. n. d.)

1.5.4 Preventative SUDS

There is also a group of SUDS that prevent stormwater from entering the ground, which are especially useful if infiltration is not possible, for reasons such as contamination or

Figure 6 Green roof (Alter 2007)

Figure 7 Water butt (Waterbut.co.uk 2011)

impermeable surfaces (Chatfield 2005). These SUDS are commonly seen in many households as rain water harvesting systems and the recycling of waste water. Green roofs (Figure 7), storage tanks and water butts (Figure 8) fall into this category (Woking Borough

Council 2004). Water stored by these methods is kept locally to where it is collected, an example being Garastor, (a storage tank that lies beneath a garage) and from which water is used for everyday tasks, such as toilet flushing and garden irrigation (Woking Borough Council 2004).

1.5.5 Permeable paving

Permeable paving can be identified by two main types of the permeable system: Infiltration and Porous (PavingExpert.com n. d.), which have been sub-divided into three surface types (Fancher *et al.* 2003), as shown in Table 2:

Table 2 Types of permeable paving surfaces

Type of paving	Description
Permeable paver block systems	Concrete paving block that have small gaps between them to allow water to infiltrate through to the sub-base and the soil.
Permeable concrete mixes	Mixes that do not include fine particles, thus creating void spaces that allow stormwater to pass through the pavement and into the sub-base and soil.
Permeable asphalt mixes	Similar to the concrete mixes, but resulting in an asphalt layer instead of concrete.

They are suitable for a range of residential, commercial and industrial purposes but are limited by the amount of usage and the weight that they can deal with (Scholz and Grabowiecki 2007). Rainfall and run-off is infiltrated through permeable material which is stored below ground. The nature of the sub-base is such that the water is briefly stored in the course layers beneath the surface and filtered slowly to prevent contamination of groundwater (Woking Borough Council 2004). Infiltration of fine particles and silt between the voids of permeable paving blocks (Figure 8) can cause an accumulation of material in the sub-base, causing clogging by sediment (Blick *et al.* 2004). It is possible to include separators in the construction of SUDS which can prevent build-up of silt and sediment. Without a separator, periodic maintenance would be required to remove blockages (NHBC Foundation 2010).

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Figure 8 Permeable Paving (Wilkinson Environmental Ltd 2010)

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Figure 9 Vegetated parking area (Barrett 2007)

The final form of PPS, not highlighted by Fancher *et al.* (2003), is paving blocks that permit the growth of grass or vegetation. Not only does the surface protect groundwater by reducing the quantity of stormwater run-off, the soil and sub-base also act as a filter that removes harmful chemicals (Sloan, Hegemann and George 2008). Usually consisting of concrete or plastic open-cell units filled with soil and topped with seed or turf (Figure 9), these pavers are designed to support the weight of vehicles by distributing the weight to prevent the compression of the soil sub-base, this in effect imitates the run-off coefficients of grass, 0.15 to 0.6 (Metropolitan Area Planning Council n.d.), which are determined by the relationship of the rainfall and runoff rates, the average intensity of rainfall (mm/hour) and the size of the drainage location (in acres) (NCDENR 2009). Mainly utilised for low-trafficked (i.e. access roads) and parking areas, the design allows air and water to pass through the soil surface (Hun-Doris 2005).

Once polluted, groundwater is difficult to clean (CIRIA 2003), thus artificial drainage systems that filter and 'cleanse' storm-water are becoming commonplace in developments, with an example (Figure 10) shown at Upton Square in Northampton, Northamptonshire.

Figure 10 A swale outside properties at Upton Square, Northampton (Harlow Council n.d.)

This eco-friendly residential development in Northamptonshire comprises 1200 homes (Brinkley 2007), and proves that SUDS (including permeable paving, swales and green roofs) can be used in a viable and attractive setting, rather than the usual conventional methods on existing housing sites (Energy Saving Trust 2006).

1.6 Soil erosion

Surface water removal and poor vegetative growth are both influenced by the quality of soil; a factor influencing successful drainage and amenity of vegetative SUDS is soil erosion.

Soil erosion is a naturally occurring process, with its intensity dependent on both natural factors and human influence (Wall, Baldwin and Shelton 2010). Erosion is just one form of degradation of soil; others which accelerate erosion include soil compaction, loss of soil structure, low organic matter, poor internal drainage, salinisation, acidity problems and pollution (Miller 2009). In VPS, stabilisation of the soil surface can be accomplished through simple measures, including reinforcement of the area using concrete or plastic open-cell units and the addition of grass or vegetation to the surface (UCDavis Extension n.d.). Reinforcement blocks could avoid surface compaction, which prevents the infiltration of water (Wall, Baldwin and Shelton 2010).

The addition of vegetation to a soil surface (i.e. swales for runoff from roadsides) provides effective erosion protection. Without vegetation cover, bare soil is susceptible to rainfall impact and splashes, and excess water is not slowed down or allowed to infiltrate (Wall, Baldwin and Shelton 2010). Vegetation is therefore seen as a means to protect the surface from water flow and erosion (Mickovski, van Beek and Salin 2005).

1.7 Grass species utilised in planted porous paving systems

Lawns and turf grasses provide benefits that protect the immediate environment; these include erosion control, protection of groundwater, improvement of air quality including dust and noise reduction, and the provision of aesthetic and recreational benefits (Chalmers and Booze-Daniels 2000). In the case of the grass surface coming into contact with high velocity flows, (for example, embankments) reinforcement of the grass should be considered so that erosion and protection are provided without the need for the traditional engineering approach of rock and reinforced concrete (Hewlett, Boorman and Bramley 1987).

In vegetative PPS, plant species are required to tolerate the function of the surface, as well as maintain aesthetic values (Napier *et al.* 2008a). For surfaces that are to withstand friction of tyres during the movement of vehicles or the trampling of feet, plant species must endure considerable wear and tear.

According to Report 116 from Hewlett, Boorman and Bramley (1987) on the 'Design of reinforced grass waterways', there are four main grass species that are used in the designs of waterways; these include *Lolium perenne* L. (perennial ryegrass), *Agrostis stolonifera* L. (creeping bent), *Poa trivialis* L. (rough-stalked meadow grass) and *Festuca rubra* L. (red fescue) (Hewlett, Boorman and Bramley 1987). These grass types are generally grown in mixtures which are recommended as they complement each other. This may be due to the improvement in coverage obtained by multiple species or perhaps that one species is deep rooting and another shallower rooting, providing stability for both species. Seed mixtures are often used for sports pitches or grass waterways (Hewlett, Boorman and Bramley 1987) where they can provide a good rooting system for erosion prevention, high wear durability or extensive surface coverage. Mixtures are therefore selected for their particular attributes, combining qualities required for the location and application.

1.8 Geovisualisation

Exploring, analysing and presenting considerable amounts of geospatial data have been enhanced using the theory, methods and tools of geovisualisation (Krisp 2006); the main advantage being that users are able to interpret data quickly, in particular from a number of perspectives (Robinson 2009). Access to multiple processes of geovisualisation enables the generation of interactive 3D maps through the use of interactive software tools (Lloyd, Dykes and Radburn 2007), providing the user with the possibility of sorting data in the search for spatial relationships and patterns (Krisp 2006). This information could forecast potential issues (i.e. in the case of this research, pollutant distribution), permitting users to use an interactive map to identify possible issues, improving preparation and response (Allen and Sanchagrin 2010).

The software platform, ArcGIS, provided geovisualisation tools to create an interactive map displaying spatial relationships between pollutant distribution and compaction of a vegetative parking surface (VPS), offering an alternative means of data presentation.

1.9 Summary and conclusions

It has been shown that SUDS can alleviate the risks of flooding and groundwater contamination, as extreme rainfall and localised flooding events have, due to climate change, become a more regular occurrence in the UK (Timlett and Gordon-Walker 2010). Subject to PPS25 guidelines, SUDS can offer developments long-term benefits, including the recharge of watercourses, the maintenance of water quality flowing through the system and environmental enhancement (Bray 2000; Wilson, Bray and Cooper 2004).

Since it is known that lawn and turf grasses protect the immediate environment, this inexpensive means of preserving the earth's surface from water flow, soil erosion and pollution prevention needs further investigation, as part of SUDS. The investigation of VPS will broadened the knowledge of their suitability for residential, commercial and industrial purposes (Scholz and Grabowiecki 2007). Previous studies have focused on the water quality and quantity of storage aspects. This research will investigate the physical surface in more detail.

1.10 Aims and Objectives

VPSs are one of four permeable paving options in the SUDS approach which are available for stormwater management. Research into the efficiency and efficacy of vegetative PPS in mitigating urban pollution is limited so the first aim determines, by means of a pot trial, possible effects that oil contamination has on a variety of grass species recommended by CIRIA (Hewlett, Boorman and Bramley 1987) for surface coverage and erosion control. Accomplishing the aim was made possible by:

- Three random blocks of triple replicate pots of four grass species were subjected to increasing volumes of used engine oil, to indicate the species' tolerance to contamination.
- Statistically analysing the difference in weights of harvested plant material, will determine if oil-contaminated compost has detrimental effect on growth.
- Determining the Median Effective Concentration (EC_{50}) at which 50% of the grass' growth was affected by oil contamination, will identify growth inhibition as a result of contamination, determining the suitability of these species for VPS application.

Combining biomass data with Seel's (unpublished Undergraduate thesis 2006) research into the pollutant contamination taken up by grass species, comparisons can be made between the grass species' suitability of contamination tolerance and other grasses in existing literature.

The second aim identifies the distribution of pollutants across the vegetative parking surface. Objectives to fulfil the second aim of this research include:

- A VPS was located and permission sought to access the site for analysis.
- Warwickshire County Council was approached for details of VPS installation and its construction.
- Using individual cells of the SCS Integra block, grid co-ordinates provided specific locations for each sampling area.
- The entire VPS to be subjected to compaction assessment; the surface pressure from each SCS Integra block cell to be tested with a penetrometer, in kg/m^2.
- Randomly-selected soil samples being assessed geochemically using ICP-MS analysis, to determine element concentrations.
- The use of magnetism techniques to characterise and profile environmental pollution proxies from soil samples, in addition to the geochemical data.
- A comparison of these data will determine any relationship(s) between components; principal component analysis and hierarchical clustering will highlight variance and comparisons in the data.

The final aim provides a simple method of presenting this small-scale spatial data using Geographical Information Systems (GIS), by:

- Using a handheld GPS receiver, position of the VPS at Clinton Primary School, Kenilworth, was acquired and enabled the identification of spatial coordinates marking sample locations and information associated with them.
- Layers display compaction, geochemical and magnetic data and with the possibility of turning these layers on and off, their spatial relationships provide a visual, informative system of trends and relationships between the features.

The following chapter explores literature on SUDS applications, in particular systems associated with roadside locations and vegetation. Chapter 2 also investigates the identification and distribution of pollutants through the use of geochemical and magnetic parameters, and identifies the use of Geographical Information Systems (GIS) to present spatially-related data in map format to distinguish relationships visually.

This research aspires to fill a gap in the knowledge of vegetative permeable paving surfaces. Permeable paving has been studied from runoff and infiltration characteristics (Acioli, da Silveira and Goldenfum 2005; Illgen *et al.* 2007), to the efficiency of different surfaces and their water managing capacities (Gomez-Ullate et al. 2010a), to retention of oil within the subbase (Newman et al. 2004) and to water quality (Coupe et al. 2005). Although vegetative surfaces such as those at roadsides (i.e. filter strips) (literature to follow in Chapter 2) have been investigated for their heavy metal concentrations and distributions in relation to traffic, VPSs have not been subjected to these analyses thus this research will add to sustainable drainage knowledge. It is predicted that the vegetative surface will be subjected to change in element concentrations and their distribution will be affected by vehicles parking on the VPS, along with compaction of the soil surface with vehicle weights parked on the bays. In addition to statistical analyses, these predictions will also be determined through the use of a Geographical Information System, which will make the data easy to visualise and interpret.

Chapter 2 Literature Review

Chapter 1 introduced how SUDS in general can form a fundamental part of the management of stormwater drainage and pollution control. This chapter focuses on vegetative parking surfaces (VPS) and explores the use of magnetism and geochemical techniques to classify and quantify elemental contamination, and the utilisation of GIS to present the distribution of pollutants. Investigations of VPS have compared water quality and storage abilities with other 'hard' standing permeable paving (Brattebo and Booth 2003; Sloan and Hegemann 2003; Acioli *et al*. 2005; Gomez-Ullate *et al*. 2010a; 2010b). Analyses of VPS and other vegetative surfaces are limited to investigations of the consequences of anthropogenic pollution, highlighting the comparisons between rural areas and urban and industrial locations. These studies investigated areas on a large scale, usually covering a city or region. As this literature covers pollution issues, it will provide data that small-scale VPS research can be compared with.

2.1 The effects of vehicle-related contamination on grasses and plants

There is extensive literature relating to the use of plants to 'clean' contaminated land and wetlands. Studies have included the use of *P. virgatum*, *F. arundinacea* and *C. cajan* which tolerated oil and increased oil degradation, leading to a reduction of soil toxicity (Vavrek and Campbell 2002); marsh plants have figured heavily in the clean-up of wetlands and coastal regions affected by marine oil spills (Pezeshki and DeLaune 1993; Nyman and Wood 1998) and as constructed wetlands to capture sediments from contaminated sites as water flows downstream (White 2001). Mixtures of soybean (*Glycine max*)/green bean (*Phaseolus vulgaris*); sunflower (*Helianthus annus*)/Indian mustard (*Brassica juncea*); mixed grasses/maize (*Zea mays*); and mixed clover (red clover, *Trifolium pratense*/ladino clover, *Trifolium repens*) have demonstrated effective phytoremediation of oil-contaminated soils (Dominguez-Rosado and Pichtel 2004). This evidence suggests that varieties of grass may provide a beneficial function in this regard. Many vegetative SUDS devices are installed in association with roads (e.g. swales) or parking (e.g. VPS) and hence Chapter 1 suggested a range of pollutants which the vegetation would need to mitigate, highlighted in Table 3.

Table 3 Pollutants associated with vehicles and emissions

Author(s)	Origin	Pollutants
Tanushree *et al*. 2011	Vehicular transport (Industrial activities)	Cu, Ni, Pb, Zn
Mmolawa, Likuku and Gaboutloeloe 2011	Vehicular emissions (Human activities) (Lithogenic occurences)	Al, Co, Cu, Fe, Pb, Mn, Ni, Zn
Aslam, Khan and Khan 2011	Vehicular emissions	Cd, Cu, Fe, Mn, Ni, Pb, Zn
Murakami *et al*. 2007	Vehicular transport Yellow road paint	Cr, Pb
Murakami, Nakajima and Furumai 2005	Vehicular transport	PAHs
Lee *et al*. 2006	Vehicular transport	Al, Ca, Cd, Co, Cr, Cu, Fe, Mg, Mn, Ni, Pb, Zn
Duong and Lee 2011	Vehicular transport Atmospheric dispersion from traffic rotaries	Cd, Cu, Ni, Pb, Zn
McKenzie *et al*. 2009	Tyres Brakes *Possibly from roadside soil contributions	Cu, Pb, Zn Ba, Cu, Fe, K*, Mg*, Mn*, Na

To focus in on studies of the effect of oil contamination, sump failures onto VPS will enable understanding of pollution and amenity consequences, as well as remediation approaches. McGrath (1992) subjected *L. perenne* cv. Vigor to increasing amounts (0, 1, 2, 4, 8, 16 and 32 g oil/100 g soil) of diesel oil contamination, identifying the ED_{50} (effective dose required for response effect in 50 % of plants) and growth reduction in a pot trial over a two-year period. Continuation of this research focused on using the grass as a test plant and demonstrated a decrease in the toxicity during the experimental period, suggesting that grass plants can tolerate and deal with contamination through biodegradation, evaporation and elution. A subsequent field experiment by McGrath (1992) simulated oil spillage on a surface of *L. multiflorum* cv. Meritra. Seven replicate treatments of 0, 1.17, 2.35, 4.70, 9.40, 18.80 and 37.60 litre per plot were applied to replicate 0.5 to 16g/100g soil loadings to simulate oil spillage on agricultural land. Determining the toxic effects and recovery times, McGrath (1992) identified that despite sward kill after initial application, the majority of the oil applied to the vegetation was biodegraded, leached or had evaporated from the plots, with complete regeneration and recovery of the sward from the treatment occurring within two years. Research by Pratt, Newman and Bond (1999) and Bond (1999) determined the retention capabilities and biodegradation of mineral oil in hard permeable paving. Understanding potential loadings managed by permeable paving and resulting tolerance and recovery by grass plants, prospective VPS may possess features that combine both.

Sharifi, Sadeghi and Akbarpour (2007) subjected six grasses to a phytotoxicity test and growth inhibition investigation. These herbaceous plants included *M. truncatular*, *B. mermis, S. seral, T. sativa, A. deserterum* and *L. ussitasimum* and were grown on an artificial soil contaminated with increasing concentrations of spent lubricating oil (25, 50, 75 and 100g spent oil/kg soil). Dose-dependent responses were exhibited by all six species, including a reduction in germination, above ground growth and biomass which were significantly different to the controls. Comparing data to other authors' results, Sharifi, Sadeghi and Akbarpour (2007) indicated that PAHs may have had an indirect secondary effect on the plants, such as the plant-water-air relationship (the movement, retention and uptake of water by a plant from soil (McCauley, Jones and Jacobsen 2005)) suggested by Renault *et al*. (2000), whereby on relationships between roots and soil microorganisms, including mycorrhizal fungi (which encourage carbon, water and nutrient exchange between plants and soil) implied by Vwioko and Fashemi (2005), and through blockage of soil pores leading to insufficient aeration and hindrance of photosynthesis (Oyedeji *et al*. 2012). Sharifi, Sadeghi and Akbarpour (2007) additionally considered Vwioko and Fashemi's (2005) suggestion that petroleum-contaminated soil reduces germination rates due to the seed surface being coated by oil.

Other soil pollution studies have recently focussed on non-grass plants. In studies of *Glycine max* (soybean) seeds sown in increasing concentrations of crude oil polluted soil, Ekpo *et al.* (2012) identified delay in germination and depression of growth at concentrations. Seeds sown in control and increasing contaminations (20ml, 40ml, 60ml and 80ml) of used oil contaminated soil germinated, with percentage emergence rates of 80%, 73.33%, 66.67%, 53.33% and 66.67% respectively. Analysing growth parameters, oil contamination had no significant affect ($p>0.05$) on plant height and leaf area in the first couple of weeks of the research, yet significantly affected these parameters ($p<0.05$) at a later stage. At all oil contamination concentrations, Ekpo *et al.* (2012) observed significant effects on leaf length and number of leaves throughout the study, and concluded that although crude oil did not have a profound effect on germination, it did affect soybean growth which would lead to economic implications.

In another study looking at the effects of spent oil contaminated soil, Agbogidi and Ilondu (2013) investigated germination and growth of *Moringa oleifera* (*Lam*.) (horse radish). Applying increasing concentrations (0.00, 1.61, 3.21, 6.43 and 8.09% (w/w)) to soil, data showed that there were significant decreases ($p<0.05$) in *M. oleifera* (*Lam.*) growth parameters in comparison to the non-treated plants, including germination (rate, days and percentage), plant height and stem diameter, biomass production, leaf number and leaf area.

To determine the effects of used diesel oil on plant germination and growth, Akujobi *et al.* (2011) subjected *Solanum melongena* (eggplant) to polluted soil, to investigate the effects on growth parameters. The eggplant was also treated with four nutrient applications (poultry waste, pig waste, cow dung and inorganic fertiliser) to determine if they had an influence on plant growth and remediation of contamination. Grown in soil contaminated with increasing concentrations of diesel oil (2, 4, 6, 8 and 10% pollution), plant parameters (height, leaf number and leaf area) exhibited adversely-affected, dose-dependent responses. Plants grown with the addition of nutrient supplements overcame the effects of diesel pollution and exhibited increase in height, leaf area and leaf number, particularly with poultry waste. Akujobi *et al.* (2011) concluded that soil contaminated with diesel oil may result in a reduction of soil fertility and thus a decrease in plant growth, which could be alleviated through addition of nutrients via fertiliser application.

Two similar investigations observed the effects of increasing oil concentrations on Nigerian weeds: *P. scrobiculatum* L. subjected to crude oil (Ogbo, Zibigha and Odogu 2009) with *P. amarus* Schum and Thonn., *H. spicigera* Lam., *S.rhombifolia* L. and *M. alternifolius* Vahl subjected to lubricating oil (Ogbo, Avwerosovwe and Odogu 2009). Like the McGrath (1992) investigation, these trials identified reductions in the height, fresh weight and leaf area of the weeds. The main purpose of the Nigerian investigations was the weeds' impact on the phytoremediation of the oil contamination. These studies show that the presence of vegetation can have a positive effect on oil-contaminated soil, a central tenet of the philosophy of SUDs.

Through investigation of a variety of species regarding their ability to withstand exposure to oil contamination, selection of the most tolerant species with ability to uptake, remove and transport pollutants from contaminated soil can provide additional retention abilities in a VPS. The full extent of used oil pollutants and their sources is extensive, thus selection of contaminants will be careful, since to explore all that have been highlighted in the literature would not be feasible. Later on in this chapter, additional information on pollutants from vehicle emissions will expand on elements including Platinum Group Elements (PGEs) and Rare Earth Elements (REEs), which have become ubiquitous as vehicle technology has advanced.

2.2 Grass Type Choice

Grass species used in SUDS devices provide stabilisation of the soil surface, prevention of erosion and encourage reduce water flow, all of which promote the filtration of pollutants and trapping of sediment to cleanse surface water. Report 116 from CIRIA (Hewlett, Boorman and Bramley 1987) suggests suitable grass species for waterway design (Table 4) and typical grass mixture percentages for low maintenance surface coverage in Table 5. Utilising complimenting grass species, these mixtures provide erosion prevention, durability and surface coverage. The following section therefore discusses the individual characteristics of the four main grass species highlighted by CIRIA (Hewlett, Boorman and Bramley 1987).

Table 4 Grass species attributes (Hewlett, Boorman and Bramley 1987)

Table 5 Typical grass mixture percentages for low-maintenance surface coverage (Hewlett, Boorman and Bramley 1987)

2.2.1 *Lolium perenne* L.

Lolium perenne L. (Fig. 11) is more commonly known as perennial or English ryegrass and

Figure 11 *Lolium perenne* L. (Manhart 2008)

belongs to the Poaceae family, relating closely to the genus Festuca (Hannaway *et al.* 1999). This tufted grass is commonly found in many locations throughout Great Britain (Beddows 1967; Bond, Davies and Turner 2007a), and is also native to Europe, temperate Asia and

North Africa and is widely dispersed throughout most continents (Hannaway *et al.* 1999). Originally sown exclusively in leys, seed distribution has possibly been due to the transport of hay along road carriageways (Bond, Davies and Turner 2007a), causing the establishment of the grass at roadsides, in gardens and meadows (Stace 1997). It is a robust and fibrous deep-rooting species, tolerating both agricultural and sporting situations (Hewlett, Boorman and Bramley 1987; Bond, Davies and Turner 2007a), but its main cultivation application is for forage (Grime, Hodgson and Hunt 1988). Preferring fertile soil, growth occurs best when combined with older swards that have been subjected to summer grazing, however, it will survive upland pastures (if lime is available in the soil) and it can tolerate salt contamination (Bond, Davies and Turner 2007a).

With its vigorous growth, fertiliser application (in particular N application) and intensive management must be maintained to obtain optimum growth of the species, thus ryegrass provides quick coverage of the surroundings, showing green plants within five days after sowing in good conditions (cool, moist soil (Beddows 1967)), and between 15 to 25 days in less favourable conditions, such as over-saturated soil (Hannaway *et al.*. 1999). Ryegrass is wind pollinated and seeds generally germinate immediately on release (Bond, Davies and Turner 2007a). It does not possess rhizomes though it does have some stolons for the generation of new plants (Hannaway *et al*. 1999). *L. perenne* L. is appropriate for soil conservation, providing good ground cover and fibrous, deep roots. It is therefore suitable for erosion control in the environment (Hannaway *et al*. 1999). It also demonstrates a high fibrosity index, showing resistance to maceration (Derrick, Moseley and Wilman 1993; Bond and Turner 2005) and can withstand trampling (Grime, Hodgson and Hunt 1988) so would possibly perform well under friction and shearing stress from vehicle tyre movement. The absence of rhizomes and few stolons means that each grass plant must grow individually from seed, thus there are no connections within the soil between each plant that may aid in binding soil to prevent erosion.

2.2.2 *Agrostis stolonifera* L.

Agrostis stolonifera L. (creeping bent) (Fig. 12) is a perennial, stoloniferous grass (Stace 1997) that has a wide array of species, with more than 200 identified (Casler *et al.* 2003; Scheef, Casler and Jung 2003). *A. stolonifera* L. is usually chosen for golf courses (Casler *et al.* 2003) as it is tolerant of close mowing heights (Scheef, Casler and Jung 2003). This grass species is found throughout Britain (Stace 1997) and is indigenous to roadsides, ditches and other habitats close to water, rough ground and gardens (Bond, Davies and Turner 2007b). It has a prostrate growth habit providing surface coverage (Scheef, Casler and Jung 2003),

Figure 12 *Agrostis stolonifera* L. (Morse 2008)

which arises from natural selection due to natural shifts in genetic composition that eliminates plants that are not adapted to the local environment (Casler *et al*. 2003). *A.*

stolonifera L. requires frequent cutting or regular grazing (Parr and Way 1984; 1988) to promote its growth as if left to establish with species that are taller growing, development is suppressed (Kydd 1964).

Unlike perennial ryegrass, *A. stolonifera* L. has well developed rhizomes and stolons below and around the surface of the soil respectively. These contribute to the stability of the plant in the soil as it has a superficial rooting system (Hewlett, Boorman and Bramley 1987), which enables it to colonise bare patches with minimum effort as both the rhizomes and the stolons produce new plants once they have grown across the soil surface. Trampling and footfall does not have an effect if the soil is dry, however, wet soil caused by standing water, leads to degradation following footfall (Bates 1935; Bond, Davies and Turner 2007b).

A. stolonifera L. prefers fertile soil (Grime, Hodgson and Hunt 1988) and if given the opportunity to grow in optimal conditions, this species shows little requirement for further fertiliser application thus requires less maintenance than ryegrass, tolerating both cold and shady conditions (Bond, Davies and Turner 2007b). Regenerating in the spring and autumn following wind pollination, the species does require moist soil conditions to grow and development is slow under unfavourable conditions (Grime, Hodgson and Hunt 1988).

2.2.3 *Poa trivialis* L.

Poa trivialis L. (rough-stalked meadow grass) (Fig. 13) exists in both annual and perennial varieties, and is widely distributed throughout the UK in various locations, including at the bottom of hedges and in field margins (Bond, Davies and Turner 2007c), open woods, marshes, ditches and moist grasslands (Clapham *et al.* 1987), and especially newly established leys (Froud-Williams, Hilton and Dixon 1986). Commonly found throughout Britain in rich, moist soils which it prefers (Bond, Davies and Turner 2007c), this species is indigenous in these grasslands (Froud-Williams, Hilton and Dixon 1986; Unwin, Browning and Smith 1990), and is a weed in winter cereals. Where swards have deteriorated through cultivation, it colonises to promote new growth regeneration (Grime, Hodgson and Hunt 1988). It is a slow-establishing, wind-pollinated species (Grime, Hodgson and Hunt 1988), but produces a tough and persistent grass with a well-developed system of rhizomes. Producing more than 1000 seeds per plant which it sheds between June and August (Froud-Williams and Ferris 1987), rough-stalked meadow grass prefers to germinate on well-drained soils that have high fertility (Hewlett, Boorman and Bramley 1987). Germinating seeds also need light so they need to be on the surface of the soil and not buried too deep, thus only those close to the soil surface and not sown in high densities will germinate (Bond, Davies and Turner 2007c). In comparison to perennial ryegrass and creeping bent grass, rough-stalked meadow grass requires exposure to the winter cold in order to stimulate flowering (Budd 1970), demonstrating a cold tolerance by the species (Grime, Hodgson and Hunt 1988).

Despite growing in marshlands and damp grasslands, rough-stalked meadow grass is relatively drought resistant (CIRIA 2003), requiring fertiliser application if the soil is not as

Figure 13 *Poa trivialis* L. (Cattlin 2011)

fertile as the plant requires (Bond, Davies and Turner 2007c). It is not susceptible to trampling and close mowing (Grime, Hodgson and Hunt 1988), explaining why is it more likely to be found in the locations previously mentioned, rather than on surfaces that experience vehicle traffic and movement. With characteristics of rapid, low growth and tolerance of damp and drought conditions, if grown in a mixture with other species that complement it (for example with *A. stolonifera* L.) and its tolerance of close mowing (Scheef, Casler and Jung 2003), saline conditions and heavy metal contamination (Bond, Davies and Turner 2007b), rough-stalked meadow grass may provide suitable perennial coverage of an overflow parking bay, particularly with infrequent usage.

2.2.4 *Festuca rubra* L.

Festuca rubra L. (Red Fescue) (Fig. 14) is a cool season species, located throughout the British Isles (Gately 2010), it requires chilled temperatures, adequate moisture and well drained, sandy soils to grow in. It can establish itself both in the sun and the shade (USDA NRCS 2002), taking 10 to 15 days in ideal conditions and 20 days under less favourable ones. It possesses short roots and narrow, in-rolled leaves (Gately 2010) and sheaths with a reddish colour at the base, producing a good sward under low fertility (Hewlett, Boorman and Bramley 1987). Although red fescue has a less developed rooting system, it is hardy and wear-resistant enough to be used in erosion control (good at binding soil (USDA NRCS 2002)), is relatively resistant to drought and requires less maintenance and fertiliser than ryegrass, as the grass is less vigorous and intolerant of close mowing (Hewlett, Boorman and Bramley 1987).

Figure 14 *Festuca rubra* L. (Hanford ARC n.d.)

This species is often chosen as it produces good quality lawns, putting greens and turf, and it also provides good ground cover for wildlife (NRCS 2002). Its good ground binding makes it suitable for stabilising waterways, banks and slopes (USDA 2006), therefore this stability may help in maintaining a good surface when used where vehicle movements occur.

2.2.5 Grass Mixtures

Grass surfaces usually consist of a number of species that complement each other, combining their best points, particularly when a single suitable species is not clear (Hewlett, Boorman and Bramley 1987). Selecting a mixture with high quality seed that is adapted to the soil conditions is important in surface establishment (Landschoot 1997), particularly to avoid inadequate surface coverage. Trenbath (1974) lists a number of reasons for mixtures which result from one or more of the following, if combined:

- Greater yield
- Lower variability of yield (season to season)
- Better biomass production during the growing season
- Less susceptibility to disease
- Improved crop quality

Soil conditions, growth physiology and suitable surface management can determine which species will be successful for the location. Earlier in this chapter, Tables 2 and 3 drew attention to attributes of the grass species and typical grass mixtures suggested for grass waterway design. However for applications like SUDs, vigorous growth is not essential as the grass would require regular maintenance (i.e. mowing). Grass Concrete Ltd. (2009) recommends three grass mixtures for different vegetative surface applications (Table 6):

Table 6 Typical grass mixtures for vegetative surface applications (Grass Concrete Ltd 2009)

The addition of Perennial Ryegrass to a mixture usually dictates how much maintenance is required on site. Inclusion of Ryegrass indicates that fertile soil conditions are required, in addition to regular surface maintenance (i.e. mowing), whereas mixtures not including the species are likely to be planted in low maintenance locations (Hewlett, Boorman and Bramley 1987).

In terms of suitability for use in a VPS, the ability of individual species to grow in oil contaminated conditions and tolerance of vehicles driving on the vegetative surface are important. The next section considers the types of pollutants associated with roadsides, providing greater understanding of contaminants that VPS could be subjected to once established.

2.3 Contamination of soils from vehicle emissions

Motor vehicles have been recognised as a key source of environmental contaminants for many years (Hewitt and Rashed 1991). Used motor oil is the resulting waste from internal combustion of lubricating oils in a vehicle's engine and has been identified as a principle source of urban pollutant associated with road runoff (Napier *et al*. 2008). Consisting of 80-90% base lubricating oil and 10-20% performance-enhancing additives, oils are transformed through breakdown of additives, contamination with combustion products and addition of metals through engine wear and tear (Irwin *et al*. 1997). Used motor oil contains a wide spectrum of components. Metals (inorganic contaminants) including lead, zinc, chromium, barium and arsenic and organic contaminants such as hydrocarbons, in particular polycyclic aromatic hydrocarbons (PAHs) (Hoffmann, Knab and Appel 1999) contribute to chronic illness and carcinogenicity with long-term exposure (Irwin *et al*. 1997), as shown in Table 7.

Table 7 Chronic illness and carcinogenicity associated with long-term exposure to PAHs (adapted Irwin *et al*. 1997)

Type / Extent of Exposure	**Health Effects**
Short-term	Eye irritation, nausea, vomiting, diarrhoea, confusion.
Chronic / Long-term	Decreased immune function, cataracts, kidney & liver damage, breathing problems, asthma-like symptoms, lung function abnormalities, skin redness and inflammation. Naphthalene – can cause red blood cell breakdown.
Carcinogenicity	Mutations, developmental malformations, tumours and cancer (PAHs binding to cellular proteins and DNA). Increased risk of skin, lung, bladder and gastrointestinal cancers over a long-term period. The EPA has classified seven PAH compounds as probable human carcinogens: benz(a)anthracene, benzo(a)pyrene, benzo(b)fluoranthene, benzo(k)fluoranthene, chrysene, dibenz(ah)anthracene, and indeno(1,2,3-cd)pyrene.
Teratogenicity	Low birth weight, premature delivery, and heart malformations. Also associated with lower IQ at age three, increased behavioural problems at ages six and eight, and childhood asthma.
Immunogenicity	Mechanisms not clear. Immunosuppression by PAHs may induce cancer.

2.3.1 PAHs

Polycyclic aromatic hydrocarbons (PAH) can occur naturally (through incomplete natural combustion of coal, oil and gas) (Townsend 1998; Crépineau-Ducoulonbier and Rychen 2003) but are more likely to be a result of anthropogenic activities. PAH sources include vehicle wear (brakes, paint, rust), emissions from exhausts, weathered materials from asphalt surfaces, petroleum and tyre particles (Takada, Onda and Ogura 1990; Pihl and Raaberg 2000; Crépineau-Ducoulonbier and Rychen 2003).

Napier *et al*. (2008) reviewed metals and PAHs in the environment, relating to four vehicular emission sources: oil leaks/spills, brake wear, tyre degradation and exhaust emissions. Amongst the most toxic, 16 PAH isomers and five heavy metals (Cu, Zn, Cd, Hg, Pb) of significant concern in aquatic environments were examined. Table 8 highlights values estimated by Napier *et al*. (2008) for the four vehicular sources following the review by Ellis and Chatfield (2000), Councell *et al*. (2004) Novotny and Olem (1994), Davis, Shokouhian and Ni (2001), (INCHEM 1998) and Coupe *et al*. (2005).

Table 8 Pollutant estimates (t) from passenger cars to the UK environment in 2003 (Napier *et al*. 2008)

Comparing data with the National Air Emissions Inventory, Napier *et al*. (2008) showed that atmospheric pollution had decreased with changes in fuel additives, whereas pollutants in marine and terrestrial systems caused by oil leaks and exhaust emissions were still of concern. Napier *et al*. (2008) concluded that traffic management, improvement in vehicle technologies and changes in drainage infrastructure (i.e. SUDS) would further aid the reduction of pollutant impacts on the environment.

2.3.2 Tyre and traffic-related pollution

Tyres and traffic-related materials (brake dust, tyre treads and yellow roadside paint) can further affect, and Adachi and Tainosho (2004) analysed 60 tyre dust samples, classifying 2288 heavy metal particles into four clusters. Table 9 specifies possible sources for the clusters determined.

Table 9 Clusters identified by Adachi and Tainosho (2004) classifying heavy metal particles from tyre dust samples

Cluster	Possible source(s)	Elements
Fe	Brake dust	Particles rich in Fe and with trace Cu, Sb, and Ba
Cr/Pb	Yellow paint	$CrPbO_4$ particles
Multiple elements (Ti, Cr, Fe, Cu, Zn, Sr, Y, Zr, Sn, Sb, Ba, La, Ce, Pb)	Brake dust	Particulate Ti, Fe, Cu, Sb, Zr, and Ba Heavy minerals Y, Zr, La, and Ce
ZnO	Tyre tread	Zinc oxide

Comparing tyre dust and tyre tread, Adachi and Tainosho (2004) confirmed that tyre dust had greater concentrations of heavy metals, in addition to Al, Si and Ca from minerals and asphalt materials. They concluded that tyre dust contained not only fragments of tyre wear, but also particles from brake lining, road paint and asphalt surfaces.

2.3.3 Roadside pollution in vegetation

Roadside pollution has been the focus of many investigations (Jaradat and Momani 1999; Amusan, Bada and Salami 2003; Akbar *et al*. 2006; Shaikh *et al*. 2006; Voegborlo and Chirgawi 2007; Ticianelli *et al*. 2009); however there have not been many related to SUDS devices. These examples investigated contamination of vegetation along roadsides that were subject to heavy metal pollution resulting from vehicle emissions, wear and corrosion of components and fluid leakage. Awareness and understanding of heavy metal toxicity in soils and vegetation is important, as planting the appropriate species for the rehabilitation of contaminated areas aids the regulation of particulates efficiently (Ghosh, Maiti and Singh 2009). Since many roadside SUDS devices are based on vegetation, the following section identifies heavy metals observed in roadside soils and the influence of traffic volume on their concentration.

2.3.3.1 Heavy metal pollution in soils

Non-biodegradable, heavy metal contamination has long residence times in soils, making transportation to groundwater or uptake by plants more likely (Boularbah *et al*. 2006). Leitão (2005), Jankaitė, Baltrėnas and Kazlausklenė (2008), and Ghosh, Maiti and Singh (2009), reviewed the effects of heavy metals on soil, vegetation and groundwater. Despite metals being natural elements and readily available in trace amounts that are essential to the ecosystem and plant metabolism, excessive levels cause toxicity, harm organisms or biota and lead to bioaccumulation in plants (Martin and Griswold 2009). Applying the SUDS triangle concept to the design of drainage systems, run-off containing toxic levels of trace elements can be directed through interconnecting SUDS in the Treatment Train, improving water quality through the processes, rather than diverting polluted water to another location.

Many studies (including Jaradat and Momani 1999; Shaikh *et al*. 2006; Voegborlo and Chirgawi 2007; Ghosh, Maiti and Singh 2009) of heavy metal contamination in road runoff and roadside pollution have concentrated on Pb, Cd, Cu, Zn and Fe. Others (including Ramakrishnaiah and Somashekar 2002; Leitão 2005; Jankaitė, Baltrėnas and Kazlausklenė 2008) have also included Cr, Mn and Ni. More unusual trace constituents usually of catalytic converter origin (da Silva *et al*. 2008) are occasionally incorporated in these studies included Ti, V, Co, As, Mo, Sn, W and Sb (Leitão 2005).

Marjanović *et al.* (2009) conducted an investigation of Cd, Co, Cu, Mn, Pb and Zn in urban soils from green areas and parks in Belgrade, to determine if there were changes in contamination levels. They found that some soil samples had significant increases in contamination (in particular Pb) in comparison to research undertaken three years previously. According to the Netherlands Soil Quality Standard, 93.3% of samples were polluted with Pb and Co, 60% were polluted with Zn and 53.3% were polluted with Cu (Marjanović *et al.* 2009). A number of Pb samples (6.7%) surpassed soil intervention values, indicating serious contamination incidences and highlighting locations requiring remediation.

Table 10 Mean metal concentrations in urban soils, obtained from cities globally (adapted from Marjanović et al. 2009)

City	Cd mg/kg	Co mg/kg	Cu mg/kg	Pb mg/kg	Mn mg/kg	Zn mg/kg
Galway	-	6	27	58	539	85
Hong Kong	0.36	3.55	16.2	88.1	-	103
Madrid	0.14	-	14	22	249	50
Hangzhou	-	9.25	36.57	46.15	415.27	116.07
Belgrade	1.8	16.5	46.3	298.6	417.6	174.2

Comparing average metal concentrations with urban soil samples obtained from other cities (see Table 10), Belgrade soil samples exhibited higher levels of contamination, in particular Pb concentrations. The main reason for high Pb levels arises from the use of leaded petrol which is still available and widely used. With Belgrade playground soil samples also indicating high contamination levels in addition to urban soils, several locations were identified as requiring remediation. Comparing data from their investigation and those from the previous study, Marjanović *et al.* (2009) concluded that urban soils may have been influenced by anthropogenic sources, such as leaded fuel, car components, exhaust and industrial emissions.

Introduction of Pb-free fuel and catalytic converters (compulsory in UK vehicles after 1993) has resulted in a decrease in Pb dust concentrations; however, the Platinum Group Elements (PGEs) have shown an increase (Hoffmann, Knab and Appel 1999). Main roads and urban areas are sources of Platinum (Pt) particulates (Alloway 2004) and surveys conducted by Hutchinson and Pearson (2004) confirmed increases of up to 90-fold in Pt accumulation in comparison with background readings. Surveying Nottingham city centre and residential area, Hutchinson and Pearson (2004) analysed Pt and Pb levels in soils and road dusts. Relating to traffic density in 1998, a mean Pt value of 160.3ng/g was detected in the city centre, compared to 30ng/g in the residential area. With a change in overall concentration levels from 0.8ng/g in 1982 to 70ng/g in 1998, it was possible to observe pollutant increases caused by catalytic converters (Hutchinson and Pearson 2004). Health risks caused by Pt have only recently become more apparent, following long-term chronic exposure (Wiseman and Zereini 2009). Uncertainty of exposure could not indicate potential health risks and despite assessments of Pt exposure, Merget and Rosner (2001) could not present evidence to contradict this. Subsequent studies by Ravindra, Bencs and van Grieken (2003) and Ek, Morrison and Rauch (2004) uncovered evidence of Pt solubility, indicating accumulation and bioavailability of Pt in groundwater, sediments and soils, before it eventually entered the food chain. Accumulating in the liver and kidneys, Pt is a known allergen (Ek, Morrison and Rauch 2004), which may be altered into more toxic complexes that have the potential to cause cellular damage, morbidity and death (Wiseman and Zereini 2009). However, continuous monitoring and research on bioavailability, behaviour and resulting toxicity is still required to fully understand the effects of PGEs.

These investigations highlight the importance of understanding the sources of heavy metal contamination, which would impact on SUDS design and implementation. Since pollution from vehicle emissions are not transported far from their source, roadside SUDS would prove useful in the filtration of stormwater and retention of pollutants.

2.3.3.2 Pollutants in roadside soils, in relation to distance from road

It was suggested by Haygarth and Jones (1992) that heavy metal particulates would be found in greater concentrations due to gravity nearer to roadside edges rather than in vegetation and street dusts further away. This statement would suggest that SUDS close to roadsides would possess high heavy metal content, as the surface is the first line of defence in trapping elements (Virginia DCR 2011). Investigations by Pratt, Mantle and Schofield (1989; 1995) determined that permeable paving surfaces were effective sediment retention and removal devices as suspended pollutants were trapped in the upper layers of the paving structure. Using SUDS management systems to trap contaminants, either through filtration by swales and filter strips or by sedimentation in detention basins, provides time for organic pollutants to degrade whilst metal pollutants remain until physically removed (i.e. phytoremediation) (Napier *et al.* 2008).

Investigating the behaviour of deposited sediments from urban surfaces, Zafra, Temprano and Tejero (2008) analysed particle build-up and wash-off characteristics during dry periods and rainfall events in Torrelavega (Spain), respectively. Over 65 days, 132 samples (vacuumed and swept-up) were collected and analysed for sediment loading (g m^{-2}), particle size distribution and moisture content. Sediment loadings increased with the number of dry days, with indications that particle size distribution tended to result in finer sediment (<125µm) during dry days. During storm events, Zafra, Temprano and Tejero (2008) determined that sediment particles of <500µm were more susceptible to being washed away by rainfall. This research was followed by investigations into pollutant presence in roadside sediment samples.

Investigations of soil pollution by heavy metals are global, with increasing number of studies in the less-developed world, for instance, Jaradat and Momani (1999) and Shaikh *et al*. (2006) both found that traffic densities have dramatically increased in Jordan and Botswana respectively. Focusing on four heavy metals, Cd, Cu, Pb and Zn, Jaradat and Momani (1999) and Shaikh *et al*. (2006) investigated concentrations at sample locations leading away from the roadside of heavily used highways. Both investigations determined that heavy metal contamination was greater at the roadside, with concentrations decreasing with distance. Two previous studies in Africa also analysed the effects of heavy metal accumulation in roadside soil and vegetation, investigating the relationship between roadside proximity and concentration of heavy metals (Ho and Tai 1988). Voegborlo and Chirgawi (2007) found that Pb, Cd, Ni, Zn, Cu, Cr concentrations decreased with increasing distance from Libyan roads; in addition, the reduction of heavy metal concentration with depth in the soil layer was also determined. Chen *et al*. (2010) investigated heavy metal contamination associated with vehicle emissions of roadside soils and vegetation in Beijing, China, and found that Cd, Cu, Pb and Zn decreased in concentration with distance from the roadside, with positive correlation between concentration and traffic volume; As, Cr and Ni did not share this trend. Comparing the sample concentrations to soil guideline values in China, Cd considerably contaminated roadside soils. Fewer Cu, Pb and Zn contaminants were concentrated in these roadside soils, with As, Ni and Cr not showing any concentrations of significance. The study also found that higher heavy metal concentrations were located downwind from the road.

Zafra, Temprano and Tejero (2011) investigated 132 sediment samples collected over a 65-day period from road surfaces in Torrelavega, Spain. Vacuumed and swept-up sediment samples were analysed to determine metallic load (resulting from braking and tyre wear), enabling the study of impact on drainage systems and receiving waters for use in perfecting the design of preventative SUDS systems. Identifying loadings (g m(-2)), particle size distribution (63-2800 microm) and concentrations, data indicated that heavy metal concentrations increased with particle diameter reduction. With the increase in sediment residence time, heavy metal concentrations also increased, however, the ratio between different sized fractions decreased (Table 11 shows heavy metal concentrations in the <63µm fraction).

Table 11 Heavy metal concentrations in the <63µm fraction

Heavy Metal	Concentration (mg kg^{-1})
Pb	350
Zn	630
Cu	124
Cr	57
Ni	56
Cd	38
Fe	3231
Mn	374
Co	51

Zafra, Temprano and Tejero (2011) also determined that heavy metal concentrations decreased with distance from the road, with data confirming an increase in ratio between size fractions and heavy metal concentrations as distance increased.

The findings from these studies confirm observations by Ho (1979), Ho and Tai (1988), Olajire and Ayodele (1997), Othman, Al-Oudat and Al-Masri (1997) and Fakayode and Owolabi (2003) who all found that concentrations of pollutants increased with increased traffic density.

2.3.3.3 Pollutants in roadside soils, in relation to traffic density

In relation to the environment that SUDS manage, each individual 'system' must be suitable for its application. Swales and filter strips can be located by highways and roadsides as they filter run-off water from high density traffic areas, which are more likely to filter greater amounts of pollutants at a greater frequency. SUDS in low density traffic (i.e. access roads and vegetative parking areas, where vehicle movement is less frequent) can maintain filtration of run-off with permeable paving. With fewer run-offs, surface water has greater time to infiltrate the VPS surface, where filtration of pollutants takes place in the soil surface and sub-base.

In addition to considering the effects of heavy metals on ecology and human health, Jankaitė, Baltrėnas and Kazlausklenė (2008) analysed the consequences of vehicle emissions, evaluating contamination of five highways in Lithuania. Similar to previous studies, the investigation revealed that the distribution of heavy metals was influenced by traffic density. Distributed evenly along the highway, heavy metal concentration was greater at roadside, with decreasing concentrations with increasing distance from the road. However metal concentrations did not exceed maximum “permissible” concentrations for Lithuania’s HN60 “Most Dangerous Chemicals” guidelines (Republic of Lithuania, Ministry of Health 2004). The concentrations were below the “Maximum Permissible Concentrations of Hazardous Chemical Substances in Soil” indicating that pollution levels alongside the road were not high, despite some results in the upper soil layers ranging between 1.3 and 6.7 times greater than background readings. Several exceptions arose, with Mn, Pb and Ni concentrations being greater away from the roadside at a few locations. Soil type, vegetation, wind direction and traffic density were highlighted to be the cause for these exceptions.

Ramakrishnaiah and Somashekar (2002) concentrated their investigation of roadside soil contamination assessment at four polluted sites and one control site in Bangalore. Sampling down to 30cm, the study focused on Pb, Zn, Cd, Ni, Cu, Cr and Mn with depth, rather than distances from the roadside. Resulting data determined that, with exception of Ni, heavy metal contamination correlated with traffic volume, with pollutant concentrations much higher at the roadside compared to a control site; Pb in particular was much higher than the control site, ranging from 70-280.5μg g^{-1} compared with 2-3μg g^{-1} with mean concentrations for the heavy metals (along with similar studies) shown in Table 12. Metal concentration decreased with depth, the top five centimetres having the highest values. This would be expected as the surface is subjected to regular, continuous vehicle emissions; pollution detected below the surface is the result of particles moving slowly down-profile in the soil.

Table 12 Average concentrations of heavy metals in roadside analyses

Author	**Cd**	**Cr**	**Cu**	**Fe**	**Mn**	**Ni**	**Pb**	**Zn**
Ramakrishnaiah and Somashekar (2002)	21.1 μg g^{-1}	45.5 μg g^{-1}	32.3 μg g^{-1}	Not analysed	205.8 μg g^{-1}	25.5 μg g^{-1}	280.5 μg g^{-1}	176.4 μg g^{-1}
Nouri and Naghipour (2002)	0.050 mg/l	Not analysed	0.164 mg/l	Not analysed	Not analysed	0.115 mg/l	2.276 mg/l	2.449 mg/l
Akbar *et al.* (2006)	1.2 μg g^{-1}	Not analysed	80.4 μg g^{-1}	Not analysed	Not analysed	Not analysed	175 μg g^{-1}	150 μg g^{-1}
Shaikh *et al.* (2006)	1.388 mg/kg	Not analysed	9.68 mg/kg	Not analysed	Not analysed	Not analysed	45.0 mg/kg	26.40 mg/kg

Research by Ticianelli et al. (2009) investigated As, Ba, Co, Cr, Sb and Zn concentrations from soil samples obtained from locations (Consolação/Rebouças Avenues; 23 de Maio Avenue and Tiradentes Avenue) of highly dense traffic in São Paulo. Some samples had greater concentration levels in comparison to soil reference values for São Paulo, as shown in Table 13. Concentration results indicated that Co, Cr and some As samples were below the Quality Reference Value. Sb and Zn, on the other hand, had high concentrations above the Prevention and Intervention Values, indicating that these locations had been influenced by

Table 13 Concentration values of metals from São Paulo sampling points compared to soil guide values determined by the Environmental Protection Agency of the State of São Paulo – CETESB (µg.g-1) (Ticianelli et al. 2009)

vehicle sources. Concentrations of Ba provided the most contaminated results for nearly all sampling locations, possibly resulting from São Paulo's natural lithology or due to organometallic compounds used in diesel smoke reduction from vehicle exhausts (Ticianelli et al. 2009). With none of the samples registering element values lower than the Quality Reference Value, data indicated poor quality soils present at each location.

Akbar *et al*. (2006) conducted a study on heavy metal contamination (Cd, Cu, Pb and Zn) in roadside soils in Northern England, analysing samples from different verge areas (border, verge, slope and ditch). Similarly to Ramakrishnaiah and Somashekar's research (2002), metal concentrations decreased with distance from the road (mean concentration values shown in Table 10). Confirmed by concentrations in a ditch by the verge with the lowest concentrations, Akbar *et al*. (2006) stated that despite the roadside soils containing higher pollutant concentrations than natural background maximum concentrations were below toxic levels according to guidelines from the Inter-Departmental Committee on the Redevelopment of Contaminated Land (1987). Lead contamination (ranging from 25.0 – 1198.0µg/g) was greatest in the soil, with Cd concentration (0.3 – 3.8µg/g) being the lowest. Despite the 35 site samples containing concentrations greater than natural British soil background levels, the values were below the 'critical trigger concentrations' of contaminated soils.

2.3.4 Heavy metals in street dusts

Heavy metal distribution does not solely result in the contamination of roadside soils. Street dusts in urban areas contain contaminants from emissions and industrial activities. A study by Charlesworth *et al*. (2003) identified and compared heavy metal contamination in areas of Birmingham and Coventry, including areas controlled by traffic lights. Statistics suggested that there was relationship between city population and heavy metal concentrations. Despite Birmingham having the larger population, mean concentrations were approximately three times higher in Coventry for Zn, Cd and Cu. At both locations, Cd and Pb were significantly correlated, and investigations into Pelican crossing locations indicated significant relationships between Pb and Ni ($p<0.01$) and Pb and Cd ($p<0.05$). Both cities' ring roads appeared to impact their environments:

- significant differences ($p<0.01$) were seen in Zn and Ni in both cities
- no significant difference was found with Cd
- significant difference between Pb in subset samples from Coventry but not Birmingham

- significant difference between Cu in subset samples from Birmingham but not Coventry

Trends identified included high heavy metal concentrations inside the Coventry ring road and at junctions controlled by traffic lights. In Birmingham, higher values were found near industrial areas, with lower concentrations in parks and residential locations. The proximity to main roads had no effect on any heavy metal concentrations, and with the exception of Zn, green spaces did not seem to influence heavy metal distribution in Birmingham, whereas in Coventry, main roads lead to significant differences between subsets for Ni and Pb. Similarly to SUDS designs being site specific to suit their environment, contamination from street dust is also likely to be site specific. Roads and junctions in Birmingham were more likely to encounter higher traffic intensities than Coventry due to physical size and population differences.

Reflecting on the use of swales and filter strips in the management of run-off, Waite (2010) conducted a pot trial at Coventry University investigating the effect of a pollutant (street dust obtained from Coventry) on the growth of different grass species (*Agrostis capillaris syn.tenuis, Agrostis stolonifera, Agrostis canina, Lolium perenne, Festuca rubra, Poa pratensis* and *Festuca arundinacea*). Applying different amounts of street dust to the grasses, analysis was performed on the compost, grass roots and shoots to determine concentrations of heavy metals (Cd, Cu, Ni, Pb and Zn). Compost cores showed that the dust remained mainly in the top, with the finest particles moving through the compost. Analysis of the roots showed that heavy metal concentrations were not enhanced, whereas concentrations in the shoots possessed a significant amount compared to compost core samples. In addition, run-off infiltration was simulated using seed trays. There was no significant difference in infiltration capabilities of the grass species, making them suitable for use in further vegetative SUDS investigations.

2.3.5 Accumulation of metals in grass species

A pot trial by Seel (2006) investigated the application of increasing oil concentrations to four grass species *Agrostis stolonifera* L., *Lolium perenne* L., *Festuca rubra* L. and *Poa trivialis* L. Similar to Waite (2010), compost and shoot samples were analysed over a three-month period to identify if oil contamination had any influence on biomass produced and heavy metal concentrations in the harvested samples. For all four species, greatest biomass was obtained from the positive (0% oil) control and pots with 1% and 2.5% oil (v/w %). Decrease in biomass production was evident for the pots with greater oil concentration applications. Geochemical analysis of the compost and shoot material proved that there was no significance in the elemental concentrations, however shoot samples identified elemental uptake and accumulation. Data from this study shows potential for vegetation to accumulate pollutants, which would make them ideal for use in SUDS to improve water quality.

This section has explored the inorganic contaminants likely to impact vegetative SUDS, in particular pollution originating from vehicle lubricants and emissions, resulting in contaminated run-off. The following section will introduce a technique used in urban contaminant studies as a proxy for heavy metal concentration. However, it also provides the opportunity to further characterise contamination distribution by taking account of the metals associated with tyre wear and used engine oil.

2.4 The use of mineral magnetism in heavy metal contamination determination

Studies of mineral magnetism have identified some possibilities that may be a useful method of identifying heavy metal contamination in urban samples. The following literature highlights examples of how magnetic techniques have been utilised in the analysis of samples, demonstrating correlation between contamination and its source(s).

Hoffmann, Knab and Appel (1999) traced the distribution of contaminants and their concentrations in soil along roadsides using magnetic proxies, including both surface and deeper soil levels. Using magnetic susceptibility (χ), the investigation identified regions in soils where pollution had been influenced by traffic at the roadside, determining whether mapping data using mineral magnetism was suitable. Hoffmann, Knab and Appel (1999) analysed a main road from Tubinger, located in SW Germany that had been selected for the volume of regular traffic (approx. 24,000 vehicles per day, peak hour queuing), as it was surrounded by grass on both sides of the road and not subjected to traffic since the road was laid. These factors provided ideal conditions to examine undisturbed pollution that had accumulated in the soil layers. The highest magnetic signals were measured approximately 2-3 m from the edge of the asphalt road surface, with the susceptibility values 10 times the background readings taken from the locality. Increased magnetic susceptibility of top soil was dominated by a magnetite-like layer. Sources for the high χ were suspected to be from traffic emissions, the by-products of asphalt wear and vehicle brakes. In comparison, areas not influenced by anthropogenic sources displayed low, constant susceptibility values of approximately $20–30\times10^{-5}$ (Hoffmann, Knab and Appel 1999).

Morton-Bermea *et al.* (2009) researched the possibility of a link between magnetic properties and heavy metal content (Cr, Cu, Fe, Ni, Pb, V and Zn) in urban soil samples of

Mexico City. Collecting 135 samples of topsoil (uppermost 2cm from the surface) and 17 background samples from surrounding rural fields, the samples were air-dried, ground and analysed using ICP-MS, in addition to mineral magnetism. Any increase in heavy metal concentration was calculated as a ratio between the concentration and the background value. In highly contaminated samples, where the susceptibility was greater than 400 x 10^{-8} m^3 kg^{-1}, a good correlation was found between susceptibility and heavy metal content, especially with Cu, Fe and Zn. These findings differed from samples where heavy metal concentrations were similar to background where there was little correlation with susceptibility. Morton-Bermea *et al.* (2009) concluded that susceptibility would give a reasonable indication of heavy metal contamination and could be used to indicate locations suitable for further investigation.

Studies of magnetic susceptibility by Canbay (2010), Kim *et al.* (2010), Lu *et al.* (2005) and Lu, Bai and Xue (2007) investigated whether mineral magnetism and heavy metal contamination were associated. Referring to heavy metal analyses by Yilmaz *et al.* (2003) and Ozkul (2003), and to magnetic susceptibility on pollution (Canbay 2008; 2009), Canbay (2010) aimed to verify the relationship between magnetic susceptibility and heavy metal contamination. Sampling rural and urban areas in the northern Turkish province of Kocaeli, Canbay (2010) investigated the extent to which industry had polluted soil. Cores were obtained from various locations that were potentially contaminated with heavy metals and χ measured at regular intervals. Canbay (2010) found that Pb, Cu and Zn had the highest concentrations at the top of the core sample, suggesting that top soil was subject to vehicle emissions and fly-ashes as possible sources of heavy metal contamination. Correlation between heavy metal concentrations and χ was poor, which correlated with studies by other researchers identified in Canbay (2010). According to Canbay (2010) high χ was associated with high metal concentrations in urban and industrial areas by anthropogenic contamination and high χ with low heavy metal concentrations indicated natural elements associated with rural areas.

Kim *et al.* (2010) also investigated the relationship between χ and heavy metal content but found that there was a strong correlation between contaminated soil and χ. This was demonstrated measuring χ, mineralogical composition and heavy metal content on 30 samples from uncontaminated forests, industrial roadsides and an abandoned mine. Higher heavy metal concentrations and χ were detected in samples obtained from industrial roadsides and the abandoned mine in comparison to the forest samples, the only exception being those with high clay content. A strong correlation was established between χ and heavy metal content for Cd, Cr, Fe, Mn, Ni, Pb and Zn; As and Cu exhibited weak correlation. This data validated Kim *et al.*'s (2010) theory, confirming that χ could be used as a heavy metal contamination indicator, as a technique for soil screening for heavy metal pollution in future research.

Determining the relationship between mineral magnetism properties and heavy metal contamination from vehicle emission, Lu *et al.* (2005) measured χ and heavy metal concentrations of 30 particulate samples acquired directly from the inner wall of vehicle exhaust pipes. Determining mean concentrations of Cd, Cu, Fe and Pb, a positive correlation was seen between the magnetic parameters and metals which increased linearly with the increased concentrations of Cu and Pb (Lu *et al*. 2005). These measurements provided an index for the detection of Cu and Pb.

Following this investigation, Lu, Bai and Xue (2007) examined the correlation between Cd, Cr, Cu, Fe, Mn, Pb and Zn concentrations in urban topsoils with magnetic properties in Luoyang, China. The study found high magnetic susceptibility values with samples from industrial areas and roadsides (313×10^{-8} m^3 kg^{-1} and 236×10^{-8} m^3 kg^{-1} respectively), and lower susceptibility values in green areas and parks (123×10^{-8} m^3 kg^{-1}). The topsoil samples were enriched with Cd, Cr, Cu, Pb and Zn, and these heavy metals demonstrated significant correlation with magnetic susceptibility and SIRM, thus hypothesised that the magnetic properties of topsoil may be used as an alternative method of identifying heavy metal contamination.

This section has identified literature that suggests that magnetic susceptibility provides an additional method of heavy metal detection in samples. This approach does not provide detection of individual elements thus indicates areas of potential heavy metal pollution for further analysis, which this research has used to try and distinguish contamination distribution across the VPS.

2.5 The use of GIS in spatial distribution of heavy metal contamination

GIS has been used as a tool to determine relationships between spatial data, usually at city or regional scales. The use of GIS to map the distribution of spatial contamination data in this research project is based on a small scale field trial. Literature available on the use of GIS discusses the mapping of spatial data over large areas. The use of GIS on a small scale makes this research a novel concept. For example, Mitsios, Golia and Floras (2003) determined the heavy metal content in agricultural soils, in Thessaly, Greece. In order to create a map of these concentrations, soil samples were obtained at a depth of 30 cm, and were analysed for soil pH, electrical conductivity, clay content (%), organic matter (Walkley-Black method) and total heavy metal concentration. Mapping the chemical and physical soil features and the concentration of heavy metals using 23 topographic diagrams, this data formed the foundation of the regional database, in accordance with Ministry of Agriculture, Fisheries and Food (MAFF) classification. The database created enabled storage of data that future heavy metal research could be compared to and was flexible enough to allow the addition of any data generated in the future (Mitsios, Golia and Floras 2003). Facchinelli, Sacchi and Mallen (2001) also based their multivariate and GIS approach at the regional scale, in Piemonte, Italy. The research investigated heavy metal concentrations, identifying if the origins were natural or anthropic and compared the resulting distribution data to the land use activities. Comparing this regional scale investigation to that of this research project, anthropic activities (i.e. the parking of vehicles on the surface) should highlight possible contamination of the vegetative surface. Unlike the research carried out by Mitsios, Golia and Floras (2003) that solely highlighted the content of heavy metals across agricultural soil, mapping heavy metals across a VPS would provide the ability to compare base readings obtained from the non-parked with data from the bays that were subjected to regular parking, creating a database that could be updated with future analyses to make a detailed study of the parking area. These data could be compared to those obtained from other VPS or PPS, or with samples taken from roadside soils. Comparison between stationary traffic and light/medium/heavy-flow traffic could be made, further clarifying contamination deposition from different degrees of movement.

Many studies using GIS often identify areas of heavy metal contamination that is a result of human activity, usually a result of industrial applications or the development of urban areas. Zhang (2006) used a combination of multivariate techniques and GIS to identify elements derived from natural sources and those due to human activity, at a city-wide scale. A total of 26 elements were analysed and classified by cluster analysis and principal component analysis. These multivariate analyses divided the elements into groups; the first derived from natural sources and the second a result of influential human activities. A map of these groups of elements identified that Cu, Pb and Zn had relatively high concentrations in locations such as the city centre, built-up residential areas and along major roads (Zhang 2006). These locations determined that the sources of heavy metal contamination were due to traffic pollution and also due to the use of coal and peat fires for heating in older built-up areas. Zhang (2006) showed that the use of spatial pollutant distributions can indicate areas where residents may be at health risk from exposure to heavy metal pollution. Analyses such as Zhang (2006) show the importance of locating the sources or sinks of heavy metal contamination, making its application to the study of contaminants distributed over an area valuable. Whether its use on a small scale is viable or not will be determined in Chapter 5.

Li *et al*. (2004) conducted an extensive survey of distribution of anthropogenic contamination by metals variations in the urban area of Kowloon, Hong Kong and identified regional. Metals were mapped using GIS, and showed strong relationships between Cu, Ni, Pb and Zn, suggesting spatial relationships of these heavy metals with common sources in the urban soils such as along roads, at junctions and around industrial areas. These sources suggest that vehicle emissions, component wear and industrial activities were the primary cause of the heavy metal pollution (Li *et al.* 2004). Chang *et al.* (2009) examined differences between road dusts and associated soil sampled from an industrial area, identifying differences between metal spatial distribution and their source. Sampling from 28 sites, road dust and soil samples were analysed for their metal concentrations. Road dusts indicated higher concentrations in comparison to those detected in soil. Average concentrations showed that Fe and Zn had the highest concentrations in both the road dust and soil. Spatial distributions between dusts and soil displayed distinct differences. Using GIS, Chang *et al.* (2009) showed that road dusts samples collected close to a steel plant had elevated levels of Fe, Pb and Zn, whereas Cr, Cu, Fe, Pb and Zn all showed increased levels in soils samples from the same location. In addition, dust samples from a road intersection had higher concentrations of Cu, Cr and Ni (Chang *et al.* 2009). Differences in the metal sources between road dusts and soils were identified using PCA, with source identification influenced by road dust metals and analysed areas influenced by soil metal data. These two applications of the use of GIS for creating maps of urban soil contamination made it possible for many locations to be analysed quickly, identifying areas of specific interest.

Lee *et al*. (2006) conducted extensive research into environmental quality in Hong Kong, sampling soil from parks and suburbs, determining locations enriched with heavy metals and plotting pollution maps. Using PCA and cluster analysis, they found different associations between trace metals (Cd, Co, Cr, Cu, Ni, Pb and Zn) and major elements (Al, Ca, Fe, Mg and Mn) and then used GIS technology to produce soil pollution maps. The resulting maps highlighted areas of Hong Kong with high metal contamination, indicating greatest concentrations in northern and western urban locations, and areas of high traffic density contributing to major anthropogenic sources.

Examining the influence of different soil types and land use, Ivezic *et al.* (2009) collected soil samples throughout Osijek-Baranja County in Croatia and analysed for their metals concentrations (Cd, Co, Mn and Mo). Seventy-four samples were analysed from different land uses and soil types, extracting Cd, Co, Mn and Mo. ANOVA determined that land use significantly influenced extracted Cd, Co and Mn, with greater concentrations extracted from forest soil than field and pasture samples (due to lower pH values), yet no significant differences shown between field and pasture samples. Different soil types showed significance for Mo concentrations (in particular those with higher pH values) but not Cd, Co and Mn. Ivezic *et al.* (2009) presented data in map form, providing a visual representation of the data alongside the statistical analyses. Maps were created using GIS, to evaluate soil quality and heavy metal availability, and to provide a base line for further information on plant and soil relationships, and future research on soil contamination and influences through the use of fertilisers.

2.6 Geovisualisation and communication

Research data regularly takes form as a series of numbers thus techniques and tools can be applied to filter and communicate data through visual representations including chart, plots and maps. Exploratory data analysis and non-spatial techniques include (but are not limited to) correlation matrices, factor analysis, PCA, clustering, correlation coefficients, using tools such as charts and plots (e.g. bar and pie charts, boxplots, scatter plots and hierarchical plots) (Lloyd 2009). Spatial/mapping tools (such as GIS) exploit data to generate maps, focussing on user-driven, interactive exploration and the ability to analyse spatio-temporal data for the display of spatial relationships (Robinson 2009). MacEachren and Kraak (2001) described geovisualisation as an approach that integrates scientific computing, cartography, image analysis, information visualisation, exploratory data analysis and GIS to deliver the presentation of spatial data through theory, methods and tools. As important tools for analysis and communication (Brandt and Jiang 2004), resulting maps permit users to explore, interact, analyse and communicate their conclusions (Voudouris and Marsh 2008).

Prior to the creation of a map, special attention must be paid to the map's intention, its target audience, where it will be used, how simplified its data needs to be and what information/symbols (data objects, coordinate systems, projections, scales) it communicates to its audience. By asking these questions, important data objects can be prioritised and a useful means of communicating information can be created (United States Environmental Protection Agency 2004).

Whilst using GIS as a tool to exhibit relationships in spatial data in map format, it was important to understand how the geovisualisation software presented data elements for communication. Interactivity is a key requirement for geovisualisation (Crampton 2002), relying greatly on computer graphics and technology for the creation, manipulation and interaction of digital objects, and allowing change of input by the user (Presley 2006; Bleisch 2012). Often relying on simple colour-based highlighting, most geovisualisation tools enable users to quickly view data elements and identify and communicate possible relationships from a number of perspectives (Robinson 2009). Through highlighting, map elements of interest can be made more prominent. Robinson (2009) identified seven highlighting styles and their communication method, which are described in Table 14.

Table 14 Seven visual highlighting styles (based on Robinson 2009)

Highlighting style	Description
Colour-based highlighting	Objects outlined or filled with colour, includes change in line widths, stroke styles, soft edging
Leader lines	Visual environments connected by labels and data objects
Depth of field	Change in contrast sharpness, visually separating objects. Focusses attention to particular object
Transparency	Attention focussed on object by dissolving context surrounding object of interest. Complexity reduced, colour and symbol information preserved
Contour lines	Multiple outlines around object, creates height effect. Changing number of contours or distance between the lines highlights effect
Colour desaturation	Objects and context visually separated. Objects of interest retain colour, others appear more grey/faded
Style reduction	Reduction in outlines, labels and graphical elements, which visually separates objects. Works with multiple graphical elements only. Removal of elements without entirely erasing object.

In addition to these styles, four interactive highlighting behaviours control the methods in which elements are viewed in geovisualisation: single, compound, categorical and

Table 15 Interactive highlighting behaviours (based on Robinson 2009)

Interactive highlighting behaviour	Description
Single	Single highlighting style applied to data object, indicating its selection
Compound	Multiple highlighting methods applied to data objects of interest
Categorical	Highlighting method of data objects and nearby context (i.e. following classification indicating objects of same classifications and their intensities)
Continuous	Highlighting style along a gradient, from one value to another

continuous highlighting (Robinson 2009). These behaviours are summarised in Table 15.

In addition to highlighting data objects with different styles and behaviours, geovisualisation applications also have a range of interactions that permit the user to explore, analyse and form conclusions on data sets. These interactions include animation, categorising, filtering/sorting, manipulation, panning, multiple views and zooming (Lloyd 2009).

Geovisualisation has become an important tool in the improvement of risk awareness and communication, in particular for complex hydrological and geomorphological processes. These processes not only can be analysed by specialists, but can provide an effective basis for communication amongst specialists and the general public (Brandt and Jiang 2004). An example of the use of geovisualisation by Brandt and Jiang (2004) for communication between hydrologists, planners and citizens, investigated downstream geomorphological changes next to the Reventazón River, following flushing of the Cachí Reservoir, Costa Rica. Constructing a digital elevation model, Brandt and Jiang (2004) surveyed volumes of deposited sediment samples following reservoir flushing and related depositions to sediment transport processes using hydrological and suspended sediment transport data (provided by hydrological stations along the river). Using both 2D and 3D geovisualisation, Brandt and Jiang (2004) demonstrated terrain erosion and sediment deposition at locations along the river, information which could have been important to a number of people: for example, farmers with agricultural fields next to the river, risk consideration for developers when planning new city areas close to the river, or those analysing hydrological studies (i.e. flooding). Geovisualisation, such as this study, would provide an important role in understanding and communicating information on geomorphological processes.

Geovisualisation was applied to storm surge models based on North Carolina hurricane strikes and were evaluated by Allen and Sanchagrin (2010) for their potential to visualise storm surges for risk awareness and communication of impending storm threats. Looking at the physical and computational limitations of the surge models, spatial representation of inhibiting factors, GIS processing and cartographic communication, geovisualisations were developed to investigate the models' appropriateness for spatial characterisation and encouraged analysis for multiple users and purposes (Allen and Sanchagrin 2010). Analysing data, Allen and Sanchagrin (2010) determined that elevation models did not incorporate features such as ditches and water management canals which could alter flooding zones (something which GIS-based elevations models could include), and downscaling of the models increased inaccuracy of inundation areas thus creating potentially imprecise data for emergency managers to work with in case of flooding. By using geovisualisation models, these inaccuracies could be overcome by offering more flexibility in data contributions and cartography. These improvements would provide more accurate information on risk awareness and communication for both emergency planners and the general public.

With the ability to turn data objects 'on and off', geovisualisation has improved the simulation, analysis and visualisation of geospatial presentations to explore data for the generation of hypotheses, development of solutions to problems and the construction of knowledge. Use of highlighting styles and their interactive behaviours have provided valuable function in the use of exploring and analysing data objects using geovisualisation tools. GIS is thus an extremely useful application in mapping the location contaminants of concern. Invaluable information can be obtained and monitored through the analysis of spatial data, promoting the continuous observations of possible pollution sources when maps are updated on a regular basis. In the case of the VPS in this research project, GIS will be used to determine the distribution of the pollutants and spatial relationships between the data.

2.7 Chapter conclusion

This chapter focused on literature, which explored vegetative surfaces and the use of geochemical and magnetism methods to quantify and classify element concentrations and the use of GIS to display pollutant distribution.

As emphasised in Section 2.2, there has been much research into plants that are used to clean contaminated soils. Many studies, including research by Dominguez-Rosado and Pitchel (2004), have investigated the effectiveness of grass mixtures in phytoremediation of oil-contaminated soils; McGrath (1992) however, focused research on a single species' tolerance of oil contamination. Individual characteristics of the four grass species have already indicated their physical suitability for surface coverage and prevention of soil erosion. An aim for this research was to determine oil tolerance of the species through a pot trial, to see if they were suitable for VPS and whether they displayed similar pollution tolerance characteristics to previous literature.

Many studies identified pollutants in soils, dusts and vegetative surface, resulting from emissions and other roadside sources (i.e. brake wear, road paints). Section 2.3 expands on studies that investigated pollutants in roadside soils and street dusts, paying particular attention to emissions from high and low density traffic, in addition to distribution of metals across roadside vegetation. Focusing on samples collected from a school car park, the second aim of this research was to identify pollutant distribution across VPS. Taking into consideration the movement of vehicles onto the parking bays, resulting geochemical and magnetic data obtained from soil samples taken from the VPS, these results could be compared to previous studies to determine if there is any correlation between vehicle movement and pollution distribution.

The final aim of this research was to use alternative means of displaying contamination distribution, making the resulting spatial data easier to differentiate. Literature mentioned in Section 2.5 focused on large scale maps that displayed spatial data covering areas such as city or regional scale (i.e. Facchinelli, Sacchi and Mallen (2001) and Mitsios, Golia and Floras (2003)). A GIS map displaying spatial data from the VPS demonstrated uniqueness to the research. Although a map at such a small scale could not be directly compared to regional-scaled maps, distribution of metals close to roads and to high/low density traffic could give an indication of how pollutants could be dispersed as vehicles drive onto VPS.

The following chapter (Chapter 3) sets up the methodology to address the aims and objectives detailed in Chapter 1. Following growth analysis of four grass species sown in oil-contaminated compost (see Chapter 4 for results), a field trial to investigate effects of contamination from vehicles on vegetative parking bays determined effects resulting element concentration data obtained from the VPS field trial will be analysed with PCA and cluster analysis, before mapping in GIS (Chapter 5). Comparing results with literature on previous studies will identify if magnetism and GIS are suitable for pollution analysis of vegetative parking bays.

Chapter 3 Methodology

Urban roadside contamination, identified in the literature review as organic and inorganic, do not move far from their source, therefore providing the opportunity for mitigation before transportation further. Vegetation has the potential to mitigate the worst impacts of some contaminants, thus the aims and objectives were set up to test whether SUDS in general and individual grass types in particular could address the water quality aspects of the SUDS Triangle. A further aim used GIS to investigate the spatial distribution of contaminants associated with parking vehicles on a vegetative surface. This chapter, therefore, details the methodology used to investigate the aims and objectives.

3.1 Introduction

A preliminary pot trial was set up to investigate the median effective concentration (EC_{50}) of increasing oil concentrations, identifying the species most tolerant to the contamination. Used oil was used in this study as not only did it contain many of the pollutants that are often found as a result of component wear and tear and vehicle emissions in roadside runoff (Haygarth and Jones 1992; Leitão 2005), but it also relates this research to other studies that observed a positive rehabilitation effect that vegetation had on oil-contaminated soil (Amusan, Bada and Salami 2003; Ogbo, Avwerosovwe and Odogu 2009). In parallel with the investigations another pot trial investigated heavy metal content of the soil sampled from pots containing increasing oil concentrations. Together with analysis on the four grass species, the resulting data formed a complete evaluation on the application of oil to a pot trial, forming the foundation for a worst-case scenario if a major oil leak occurred on a VPS (Seel 2006).

The second section in this chapter describes the field trial in which soil samples were selected from a regularly used VPS located at a primary school in Warwickshire. Due to space and financial constraints to design and build an experimental vegetative parking area with a grass surface (species determined by pot trial results) at the university campus, a vegetative car park with the desired grass surface was locally sought to provide soil samples for analysis. Used oil was not applied to the VPS as distribution of elements caused by vehicles parking on the surface was sought after, rather than investigating its pollutant effect on grass growth which was determined by the pot trial. Once a suitable site had been located, the entire surface was subject to compaction evaluation and samples were subjected to geochemical analysis and magnetic measurements. These techniques determined the pollutants' concentrations and spatial distribution as well as investigating whether magnetism could be proxy for heavy metal contamination.

To finalise the novelty of this research, the data has been presented as an interactive map using Geographical Information Systems (GIS) software. The literature reviews (Section 2.5) showed how GIS has been used to record spatial data at the city or regional scales with very few studies using the technology at the scale of an individual car parking space.

Vegetative parking surfaces form a small part of the SUDS family. Despite many studies on the use of vegetation in swales and filtration strips, limited research has taken place on vegetative parking areas. As highlighted in Chapter 2, recent investigations on vegetative PPS have concentrated on water quality and storage abilities when compared with other 'hard' standing permeable paving (Acioli *et al*. 2005; Gomez-Ullate *et al*. 2010a; 2010b), however this study presents data on both the vegetation and soil of a VPS aspects, which have not been investigated before.

3.2 Preliminary pot trial to assess the growth of four grass species in oil-contaminated growth medium

Small-scale laboratory trials allow the sort of experimental control not able to be exerted at the field scale, thus the pot trial was designed to assess the effects that oil contamination had on the growth of four grass species.

The species that were chosen for the preliminary analysis in this study included: *Agrostis stolonifera* L. (Creeping bent), *Festuca rubra* L. (Creeping red fescue), *Lolium perenne* L. (Perennial ryegrass) and *Poa trivialis* L. (Rough meadow grass) (Herbiseed, Twyford). As wild types, these grasses still retain their natural characteristics as they have not been subjected to breeding, making them ideal for analysis. As mentioned in Chapter 2, these species were chosen as recommended in CIRIA Report 116 (Hewlett, Boorman and Bramley 1987), for their use in the design of reinforced grass waterways, as they provided low maintenance erosion control and surface coverage (Hewlett, Boorman and Bramley 1987) which suggests that they may withstand shearing and wear from vehicle tyres when incorporated in a VPS. However, each of these species were tested separately in this investigation for their ability to grow in oil-contaminated John Innes No. 1 compost (B&Q, Coventry), determining if increasing volumes of used oil (Lota Garage, Gosford Street, Coventry) applied to the compost had different effects on the species. Studies such as the interaction between individual grass species and soil nutrient status (Vinton and Burke 1995), the biotic interactions that individual plants have on ecosystems (Wardle *et al*. 2002) and the response of non-target plants to pesticides (Karthikeyan *et al.* 2003) have shown that individual species react differently to one another. With the exception of the parallel study by Seel (2006), little is known of the effects of subjecting individual grass species to oil contamination.

3.3 Seed Application Proportion

The pot trial was designed to test the effects that the addition of increasing volumes of oil contamination to the compost for determination of whether a particular grass was more tolerant of contamination presence. Using pots of a size to produce sufficient grass grow for sampling, 250 g of John Innes No. 1 compost was added to each pot and seeds of the four grass species were weighed out in the amounts shown in Table 16 and sown on the compost surface. Set grass sowing densities were recommended by STRI (Sports Turf Research Institute) to attain healthy surface coverage, sufficient re-growth for repeat harvests, and to maintain real life representation of a vegetative surface (Waite 2010).

Table 16 Weight of seeds sown on the compost surface (Waite 2010)

The following flow chart (Figure 15) portrays the steps taken in the pot trial methodology. Grasses were grown and harvested over a period of six months; Figure 16 represents the pot arrangement.

John Innes No. 1 compost: 250 g per pot

Oil treatments applied to compost: 0ml (seeds and no oil: positive control), 2.5ml, 6.25ml, 12.5ml, 25ml, 50ml oil

(0%, 1%, 2.5%, 5%, 10% and 20% v/w respectively) - food mixer to assure thorough mixing

Series of pots with oil treatments and no seeds (negative control)

Seeds sown on surface (refer to Table 1 for amount required)

Pots arranged in three Cyclic Latin Square blocks (Fig 16)

Adjust temperature 24°C ± 2°C, watered daily to field capacity

Harvest every 28 days, at the base of the grass shoots

Fresh sample weight, dried for three days at 80°C and dry weight recorded

Moisture content lost determined (see Chapter 3.3, p66)

Figure 15 Flow chart of the pot trial methodology

Block 1

Negative control	0	1	2.5	5	10	20	*P. trivialis*	5	20	1	10	0	2.5
F. rubra	20	10	5	2.5	1	0	*L. perenne*	10	2.5	20	0	5	1
A. stolonifera	1	0	10	20	2.5	5							

Block 2

P. trivialis	10	1	20	2.5	5	0	*A. stolonifera*	2.5	10	5	0	20	1
Negative control	1	5	0	20	2.5	10	*F. rubra*	5	20	1	10	0	2.5
L. perenne	20	0	10	5	1	2.5							

Block 3

L. perenne	5	1	0	10	2.5	20	Negative control	20	2.5	10	1	0	5
A. stolonifera	0	5	20	2.5	1	10	*P. trivialis*	1	20	5	0	10	2.5
F. rubra	10	0	2.5	5	20	1							

Figure 16 Cyclic Latin Square block design of the pot trial (three pots per treatment, values represent oil v/w %)

A Cyclic Latin Square ensured comparison between grass species and oil contamination variables, taking into account edge factors (i.e. temperature, air movement and light intensity (Waite 2010)), whilst adhering to requirements that each row and column equally contained all treatments in each block plot (Horsley 2003; Bailey 2008). Available greenhouse space prevented a rectangular pot layout thus the blocks were formed in the arrangement as shown in Figure 16.

Each pot was watered with deionised water daily until field capacity was attained. Field capacity is the volume of water that a soil can retain following saturation, prior to drainage by gravity, which is available for crop water uptake and evaporation (Nachabe 1998). Water was added to the surface until seepage occurred from the pot base. Gravitational movement of water in the pots imitates, on a small scale, percolation of rain water through large pores from the surface to sub-soil, leaving it saturated. Once gravitational water drains away, soil is left at field capacity and plants draw water through capillary pores until no more is withdrawn (Better Soils n.d.).

Analysis to determine the effect that the oil had on the growth of the grass species involved the grass blades and stems being harvested every 28 days, cutting stems above the compost surface to maintain a standardised method. Immediately after harvesting, the fresh samples were weighed using a top-pan balance, then placed in pre-weighed paper bags and placed in an 80°C oven for three days to dry. After re-weighing, moisture content lost from dried samples (due to evaporation) determined biomass produced, represented by sample weight loss. The weight measurements were analysed using ANOVA and regression in Microsoft Excel 2007 to statistically determine if the contaminated compost had had an effect on the growth of the grass species. ANOVA was used to establish the means of observations, before comparing the variance of these means with the average variance in each group. It was assumed that observations had the same variance and that populations were normally distributed and that each value was sampled independently from the others. Stating that observations in different groups had the same means, the null hypothesis clarified that variance amongst the groups would be the same as within groups, thus as means get further apart, variance amongst the means increased (McDonald 2009). The Tukey-Kramer method also provided additional data on the determining the significant difference between means, utilising post-hoc analysis to report patterns between sub-groups of sampled populations.

Regression determined if the relationship between the growth of four grass species and growth in increasing volumes of oil contamination was significant. Data was plotted as scatter points on a chart, and a line that best fit the points indicated provided a visual summary of the relationship. If the slope of the line was significantly different from zero on the chart, a significant relationship was verified between the variables. Hypothesising that increases in oil contamination caused an effect on the growth of different grass species, the

R^2 coefficient of determination indicated the strength of the relationship between the variables (values near to 1 almost fitting the regression line thus a strong association; values near to 0 having little relationship) (McDonald 2009). These analyses were fulfilled in the analyses in this research and their results can be found in Chapters 4 and 5.

The cumulative weight of the harvested samples was analysed, to establish if growth occurred at a similar rate throughout the experiment, along with determining the Median Effective Concentration (EC_{50}) at which 50% of the grass' growth was affected by oil contamination.

3.4 Heavy metal distribution in plants and compost

An opportunity arose during the research, to supervise and work alongside an ERASMUS undergraduate student. Providing laboratory experience, the student undertook an experiment in which four grass species and compost samples were analysed for heavy metal and element distribution, following contamination of the compost with increasing volumes of oil. The methodology followed that of the preliminary pot trial shown in the flow chart in Figure 15. Geochemical analysis of the plant material and the compost included the digestion of the samples (grass samples: 5ml nitric acid; compost samples: 3ml nitric acid, 2ml hydrogen peroxide – see Figure 27 for method, Page 92) subjecting them to ICP-MS analysis for pollutant content. Due to the amount of samples and the time constraints imposed on the investigation, hydrocarbons were not analysed as part of the study.

3.5 Vegetative paving field trial

Subjecting grass species to an increasing oil contamination pot trial provided the possibility of determining additional characteristics to those shown in Section 2.2. With the ability to control the testing environment, including temperature and water distribution, pot trials make it possible to research numerous variables in relatively small spaces. The pot trial in this research, however, does not have the ability to take into account the effects that vehicles would have on a VPS, which is where a field trial provides the additional research options.

The main difference with a field trial is that it provides data which is obtained from a site that has been exposed to natural environmental conditions, including rainfall, climate and in the case of this research, vehicle emissions. Simulating real life, the VPS field trial provided not only the extra spaces for vehicle parking, but also the additional resource of a reinforced, vegetative surface from which the soil samples were obtained for analysis. The Clinton Primary VPS was installed with a ryegrass surface thus data could be compared to ryegrass data from the pot trial.

3.5.1 Selection of field trial site

It was important to select a VPS that would suit the research requirements; this included having a vegetative surface of one of the four grass species, was reinforced to support regular vehicle movement on the surface and had sufficient surface area for randomised sampling. The VPS at Clinton Primary School (Fig. 17) consisted of five self-contained vegetative bays, which provided atypical-frequency (overflow) parking spaces by staff and visitors to the school, when the impermeable asphalt parking areas were occupied. Further details regarding the school are in Section 3.5.2.

Figure 17 Clinton Primary School Vegetative Parking Surface

Another VPS in the local area was located at Kenilworth High School, and although not installed at the same time as the VPS at Clinton Primary (installed early 2006), both VPSs had a similar construction (Reading per comm.). In comparison, there are three times the number of vegetative parking bays at Kenilworth High (subjected to daily use) compared to the five bays used as overflow parking at Clinton Primary, thus Clinton Primary's VPS was for analysis as it was of a more manageable size than that at Kenilworth High School. Each SCS Integra® block consisted of 6x6 smaller 'cells', as shown in Figure 20. Determining the total number of individual 'cells' across the sampling surface as approximately 9000 cells, a decision to analyse 5% of the total area was made, ensuring that the 5% were randomly selected from the surface (as described later in this chapter).

As can been seen in Figure 17, car park users had the choice of five parking bays. The area was designed for overflow parking usage of which was assessed via a survey of the staff, described in Section 3.11.

3.5.2 Location of the VPS and its construction/microtopography

Clinton Primary is a small school with 209 pupils and 25 staff and is located on Caesar Road on the south-west side of Kenilworth, Warwickshire (Clinton Primary n.d.), grid reference 52.3389, -1.587114 (Google Maps). Figures 18 and 19 (EDINA Digimap 2011) indicate the location of the primary school and the vegetative parking bays on the school site respectively.

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Figure 18 Map of Kenilworth (Scale 1:20000)

Figure 19 Map of Clinton Primary School site (Scale 1:1250)

The school car park consisted mainly of impermeable asphalt parking bays, with five grass-surface parking bays which used to be a lawn in front of the school offices but were utilised as an overspill parking area for both staff and visitors, expecting atypical frequency in use. However, this overspill parking wore the grass surface out leading to Warwickshire County Council making the decision to replace the turf with a more durable, reinforced solution.

The overspill grass area was dug up and replaced with 200mm MOT Type 1 sub-base and reinforced with SCS Integra® blocks (Source Control Systems Ltd.) for stability. The SCS Integra® blocks

Figure 20 SCS Integra® Block filled with gravel and vegetation (Source Control Systems Ltd. 2010) measure 500 x 500 x 70 mm, each weighing 1.9 kg and withstanding a compressive strength of 2400 KN/m^2 once filled (Figure 20).

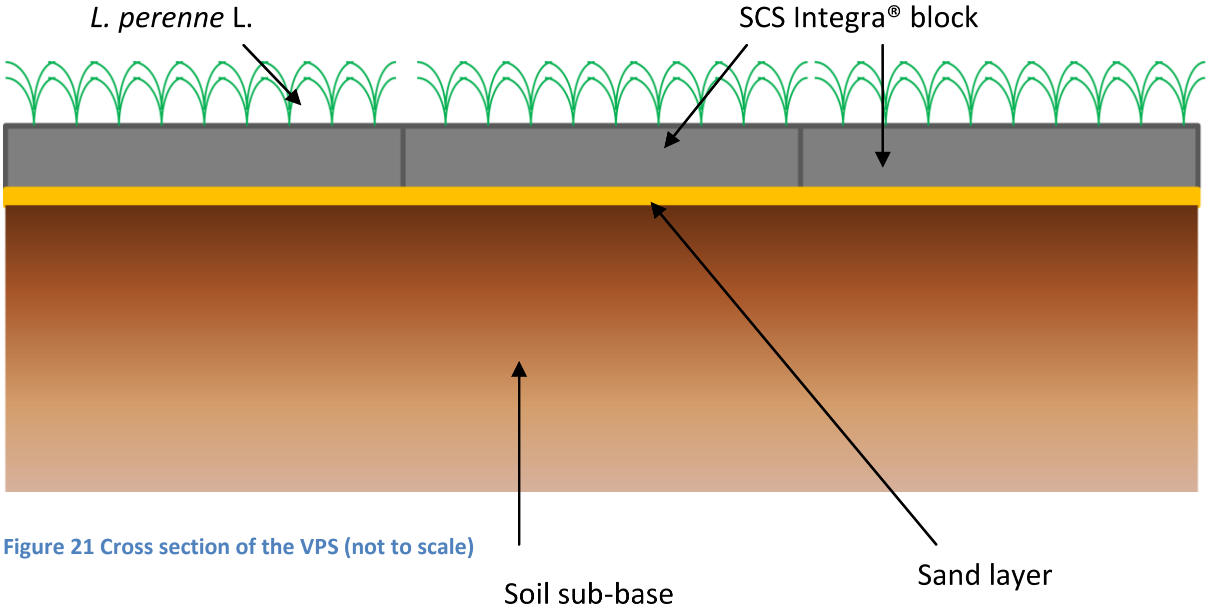

Figure 21 Cross section of the VPS (not to scale)

Typically used for access roads, vehicle hard-standings and car parks, the SCS Integra® blocks provide a high porosity, sustainable drainage solution with an infiltration rate of >5000 mm/hr (Source Control Systems 2008). The SCS Integra® blocks were re-filled with topsoil and gravel stones (both from Messrs Bartlett's Ltd., Coventry) and reseeded with high-wearing Ryegrass seeds (Hinton's Nurseries, Warwick). Figure 21 shows a cross section of the VPS and its sub-base installed by SOL Construction Ltd. and Figure 22 shows a schematic diagram of the grass-surface parking bays.

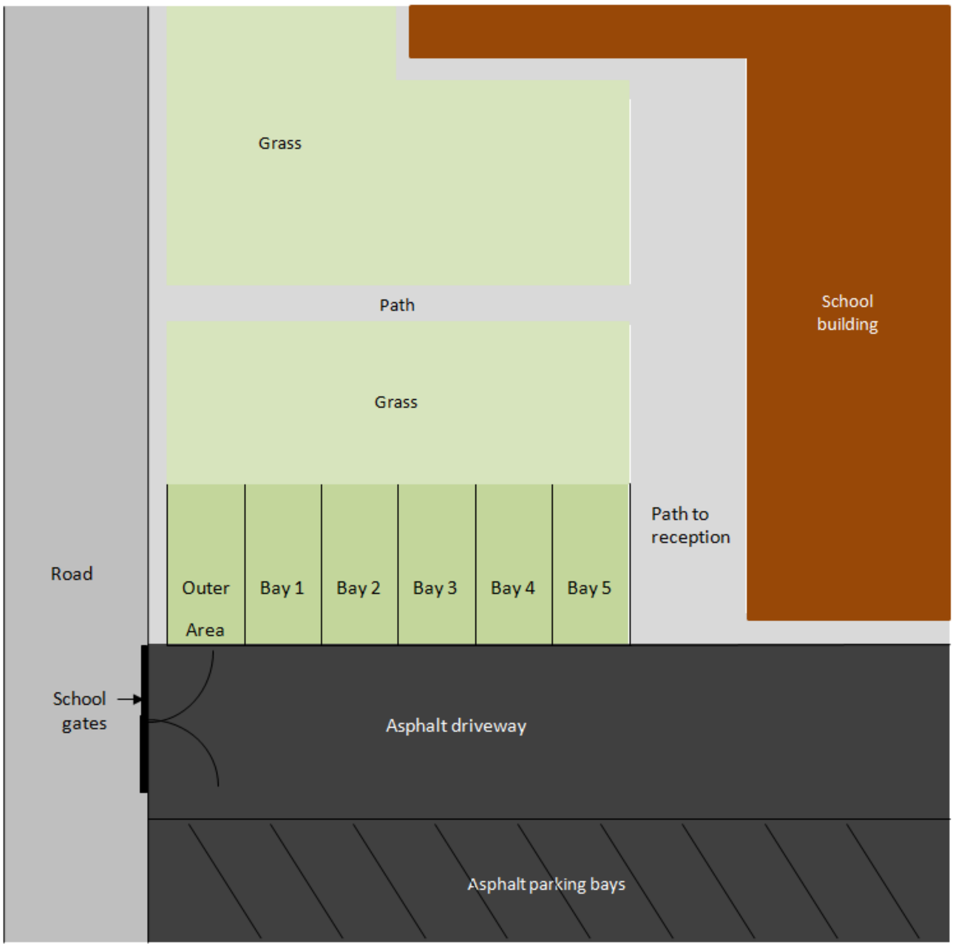

Figure 22 Schematic diagram of Clinton Primary School site (not to scale)

3.6 Compaction determination and sample selection

Soil compaction can play a part in the reduction of water and soil quality, through the increase in runoff and the destruction in soil structure, which also results in the diminution of plant yield by reducing the pore space of the soil, causing the reduction of oxygen and water, which is essential for grass roots growth (Miles 2007). With cars parking regularly on the VPS, degradation of the parking area soil surface is possible. Compaction was measured with a pocket penetrometer (Cole-Parmer Ltd., Figure 23) to determine the surface compaction across the parking area (with possible error of up to 0.124 kg cm^{-1}

Figure 23 Pocket penetrometer (Cole-Parmer Ltd.)

(Humboldt Mfg. Co. 2009)) and to assess any relationship between the bays and the non-parked control area. For each individual cell of the SCS Integra® block, the penetrometer piston was pushed into the surface of the soil. Upon reaching the calibration mark on the piston, the piston indicating ring on the penetrometer gave the strength of the compaction in kg cm^{-1}. By measuring the compaction across the area of the grass parking bays, it would be possible to locate change in compaction levels, with the intention of comparing the results with the parking habits indicated by the questionnaires and the resulting chemical data from the soil analyses. Background compaction data were collated from the non-parked section of the VPS and from the school lawn adjacent to the VPS, enabling the compaction comparison between the surfaces. The extensive compaction data can be found in the 'Data' file in the additional Appendices disk at the back of this thesis.

Ensuring samples were selected for non-biased results; the parking surface was divided by the individual SCS Integra® cells and each given a numerical reference for future location. The total number of possible sampling locations was subjected to a random number generator (Urbaniak and Plous 1997) and randomly-selected numbers identified locations to sample from, totalling 5 % of the parking surface. The top 3 cm layer of soil was sampled and replaced with topsoil and *L. perenne* L. seeds.

Once the soil samples had been collected, they were placed in 80°C for three days to dry and then bulk density measured using Equation 1 (Page 86).

$$Density\ (g/cc) = \frac{Weight}{Volume}$$

Equation 1 Bulk Density (http://www.geology.iupui.edu/research/SoilsLab/procedures/bulk/Index.htm)

The soil samples were then sieved to <63 µm and homogenised so they formed a dust, providing the greatest surface area of the sample. The samples were transferred to pre-weighed plastic magnetic pots, where they were packed as full as possible and were given codes that corresponded with the sample locations. Actual sample weights were determined through the calculation of the combined sample and pot weight, minus the pot weight.

3.7 Mineral magnetic measurements

Chapter 2 discussed whether mineral magnetism could be used as an alternative method of identifying heavy metal contamination in urban samples. It has been used to trace contaminant distribution, identifying areas of similar pollutant influence (Hoffman, Knab and Appel 1999) in a quick and non-destructive approach.

The magnetic susceptibility of each sample was measured using a Bartington MS2 meter (precision: 1 x 10^{-5} SI). Low and high frequency mass specific susceptibilities were both measured (χlf and χhf respectively), followed by Isothermal Remanent Magnetism (IRM) and Backfield Isothermal Remanent Magnetism (Backfield IRM). To obtain the data from the IRM and Backfield IRM analyses, each sample was placed in the Molspin Spinner, which with the use of the attached computer, produced the results. The following flow charts (Figures 24-26) show the steps required (based on Dearing 1999).

Prepare samples: remove gravel, sieve soil to <63µm, pack in pre-weighed magnetism pots (10cm^3)

↓

Prepare Bartington MS2 for analysis stability
15 min warm up period
Measurements set to 0.1 SI

↓

Change mode to 'Z' position for calibration

↓

Change mode to 'M' position for data measuring (check for drift and recalibrate when required)
Low frequency (lf) measured first

↓

Record first reading: air measurement
Place pot containing sample in the coil

↓

Ignore second reading: air and sample measurement

↓

Record third reading: sample measurement
Remove pot containing sample from the coil

↓

Ignore fourth reading: sample and air measurement

↓

Record fifth reading: air measurement
Use as the first measurement for the next sample and follow steps until complete

↓

Change mode back to 'Z'position for calibration
Change settings to measure high frequency (hf)
Allow equipment stability period (15 min)

↓

Change mode to 'M' position for data measuring (check for drift and recalibrate when required)

↓

Follow the procedure again until data measurement completed

Figure 24 Magnetism methodology for χlf and χhf

Turn on and allow equipment stability (15 min)

Adjust settings

- Attenuator altered to 1, calibration set to 928
- 'Set Gain' set to the maximum
- Short spin required

Spin calibration sample; resulting 'Easting' reading must be >0 and <20

(adjust casing by twisting, if required)

Spin sample and record data

(recalibrate every 10 samples)

If no spin obtained, adjust attenuation and calibration figure:

928 for Attenuation set at ‘1’

92.8 for Attenuation set at ‘10’

9.28 for Attenuation set at ‘100’

0.928 for Attenuation set at ‘1000 '

Enter data into spreadsheet (Appendix #) for results analysis

Figure 25 Molspin Spinner Magnetometer methodology

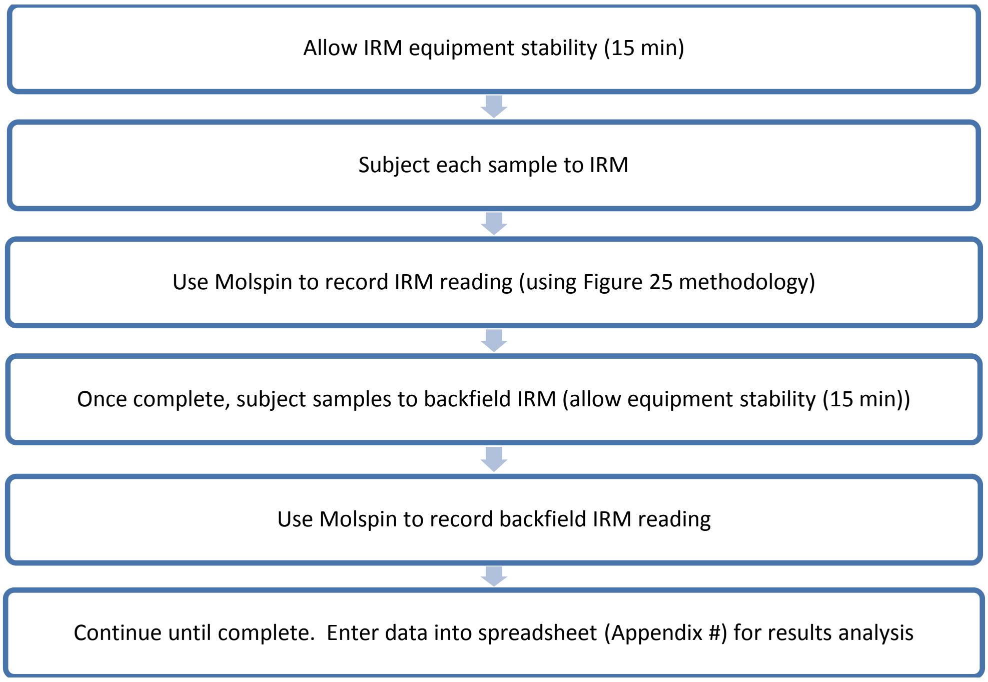

Figure 26 Magnetism methodology for IRM and backfield IRM

3.8 Geochemical analysis of the sample for pollutant concentration determination

Following the completion of magnetism analyses, geochemical analysis of the samples was carried out to determine pollutant concentrations. To use the ICP-MS for analysis of the samples, the elements needed to be dissolved. With the soil samples in a homogenised state, approximately 0.5 g of the material was weighed out, noting the exact weight each time. Each sample was transferred to a microwave vessel, prior to the addition of 5 ml trace analysis grade nitric acid (NHO_3). A positive control (spike) was prepared by including 0.25 ml (5 ppm) of each chemical element (from a 1000 ppm stock solution) to be analysed to 5 ml trace analysis grade nitric acid, in a separate microwave vessel. The negative control consisted of solely 5 ml trace analysis grade nitric acid. The microwave program is located in Appendix I. The vessels' contents were transferred to 50 ml volumetric flasks, after filtering the samples through Whatman Grade 1 filter paper to remove any remaining soil solids. Deionised water (DI) was added to each flask to make each sample up to a volume of 50 ml, mixing thoroughly. The ICP was set up to average three readings.

To determine the actual concentration of the calibration standards, rough standards of the elements were examined. Readings provided the range at which the optimum concentrations would be achieved and the true standards were created in 100 ml volumetric flasks, with a series of increasing elemental concentrations. Ten millilitres of NHO_3 (equivalent to double the volume of the samples) was added to the flasks, each of which was made up with DI water to 100 ml. The concentrations of the true standards' element concentrations (as ppm) were included in the computational method.

On completion of the method, the ICP was calibrated with the blank (10 ml NHO_3, made up to 100 ml with DI water) and the true standards, followed by sample analysis. On completion of the analysis of all the samples, the data was reprocessed to ensure that the elemental readings were on the line of best fit of the wavelength peaks. The following flow chart shows a step-by-step procedure for geochemical analysis (Figure 27).

Homogenise samples

Calibrate pipettes for accuracy

Put approximately 0.5 g of sample in microwave vessel (note exact weight), add 5 ml trace analysis grade NHO_3

Prepare positive spike: 5 ml trace analysis grade NHO_3 plus 0.25 ml (5 ppm) of each element from 1000 ppm stock

Prepare negative spike: 5 ml trace analysis grade NHO_3

Subject vessels to PEAT program (See Appendix IA) to digest samples

Using a funnel and Whatman Grade 1 filter paper, transfer sample to 50 ml volumetric flask

Add DI water to flask, making the sample up to 50 ml and mix thoroughly

Create increasing concentration standard solutions for the calibration curve

Analyse samples, determining elemental concentration against the calibration curve

Figure 27 Geochemical analysis methodology

3.9 Analysis of data (PCA, hierarchical cluster analysis, boxplots)

To reduce the numerous variables into a more manageable number, compaction, magnetism and geochemical data were analysed with PCA using the Varimax rotation method, a technique that aims to reduce the number of variables that have high loadings on each factor, simplifying the interpretation of factors (Pallant 2010). An Eigenvalue of 1 identified factors representing the majority of variance, thus allowing the elimination of surplus data. Scree plots of each sampling location confirmed the components retained, highlighting the first two components as capturing the most variance. The Rotated Component Matrix using Varimax rotation with Kaiser Normalisation, which includes the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy test, identifies and considers factors with values of 0.5 to 1 to be suitable for analysis (Williams, Onsman and Brown 2010). Showing results in a more easily interpreted pattern, the first two components from each sampling location were plotted on a scatter chart to determine similarities between the variables. Relationships between the variables were also examined, with hierarchical cluster analysis showing which variables had similar values by clustering them together into subsets, starting with single elements and merging them together into larger clusters, known as agglomerative clustering (Mooi and Sarstedt 2011). Using the Ward Method, the distances between clusters were evaluated by an analysis of variance approach; clusters were formed as shown by the changes in the agglomeration coefficients. This method calculated the total sum of the squared deviations from the mean data of the cluster (Burns and Burns 2008). These data were supported by a dendrogram; a diagrammatical representation of the similarity and distance between the clusters (Mooi and Sarstedt 2011), comparing mean similarities of variables in the same category to mean similarities of variables in a different category (van Sickle 1997). Exploring large data sets using graphical displays, such as bar charts and histograms, often leads to diagrams that contain too much detail (The Open University 2011), particularly if a single set of data is under scrutiny. Boxplots provide a graphical representation of quantitative data, as the distribution of data is displayed in a standardised method (Aaiyar 2008). Boxplots comprise of minimum and maximum values (shown as whiskers and hinges/fences at either end of the box), the median (or typical) value,and the interquartile variable range (IQR) with includes the first and third quartiles (Lane 2008). In addition to the full variation range, extremely high maximum values and low minimum values as displayed as outliers (outside values as circles and far out values as asterisks) which lie outside of the whiskers (Griffith 2007; Lane 2008). These values represent data dispersion through the range and the interquartile range, including data skewness (Hunt 2012).

One-way ANOVA analyses a single categorical independent value (in this case, the bays and the non-parked, control area) with a single continuous/dependent variable (for example, an element or the compaction values) (PsychConnections.com n.d.). By comparing the variables individually between the sampling locations using Tukey's post-hoc tests, it is possible to determine if there is variance within or between groups. If the F ratio score results in a value less than 0.05, groups are concluded as being significantly different from another.

3.10 Mapping of data in Geographical Information Systems

Once all compaction, magnetism and element results were collected, data was collated in a Microsoft Excel 2003 worksheet in preparation for them to be uploaded for the production of an interactive map of the parking area. Specialist software from ESRI, ArcGIS, provided built-in applications for designing and managing data for visualisation and analysis of results. Three ArcGIS applications which made the analysis of spatial data easier to interpret were ArcMap, ArcGIS Spatial Analysis and ArcGIS 3D Analyst (Heywood, Cornelius and Carver 2006), which are described in Table 17.

Table 16 ArcGIS Application Descriptions (Heywood, Cornelius and Carver 2006)

Mapping spatial data, each sample was given an x, y coordinate (obtained from mapping the school location in EDINA Digimap® (nominal accuracy to 1m at 99% confidence level (Ordinance Survey 2009)), and from readings from a GPS receiver (accurate to 5m)) relating to the British National Grid Coordinate System, which made it possible to identify spatial entities at given locations (Heywood, Cornelius and Carver 2006). By creating the map with the data in x, y coordinates (accurate to 0.000000001 degrees), it permitted accessibility to the map for anyone who wished to study data information from the location.

Downloading a MasterMap .gzip file of the school's perimeter from EDINA Digimap® and uploading it into ArcGIS® (an integrated collection of GIS software products) provided a target topography layer for the first step of an interactive map. In addition to the school perimeter, building locations and local road networks were identified in this file. The grass parking bays were a recent installation thus did not exist on the EDINA map. This was overcome by adding polygons to the layer at the estimated locations for each bay followed by the points for the sampling locations, positioned with the x, y coordinates. Each sample (compaction/magnetic/geochemical data) coordinate was coded and logged in a spreadsheet in Microsoft Excel 2003 in preparation for upload to ArcGIS as individual point layers. ArcGIS then enables the user to turn each map component on and off, highlighting the layer accordingly.

Data plotted as points can be difficult to differentiate so converting them to contours can make distinguishing them easier. The points were converted to a raster dataset, and then with the 3D Analyst, the rasters were converted to Triangular Irregular Networks (TINs) and then to a contour with Surface Analysis (Heywood, Cornelius and Carver 2006). To make the map an easy-accessible file for viewing and transferring to other users, the spatial data was exported as a .pdf (Portable Document File), which was created with the ability to turn the layers 'on' and 'off' so comparisons could be made between the factors and allowing the flexibility to utilise the map without the need for the specific software. The following flow chart shows a step-by-step procedure for GIS analysis (Figure 28).

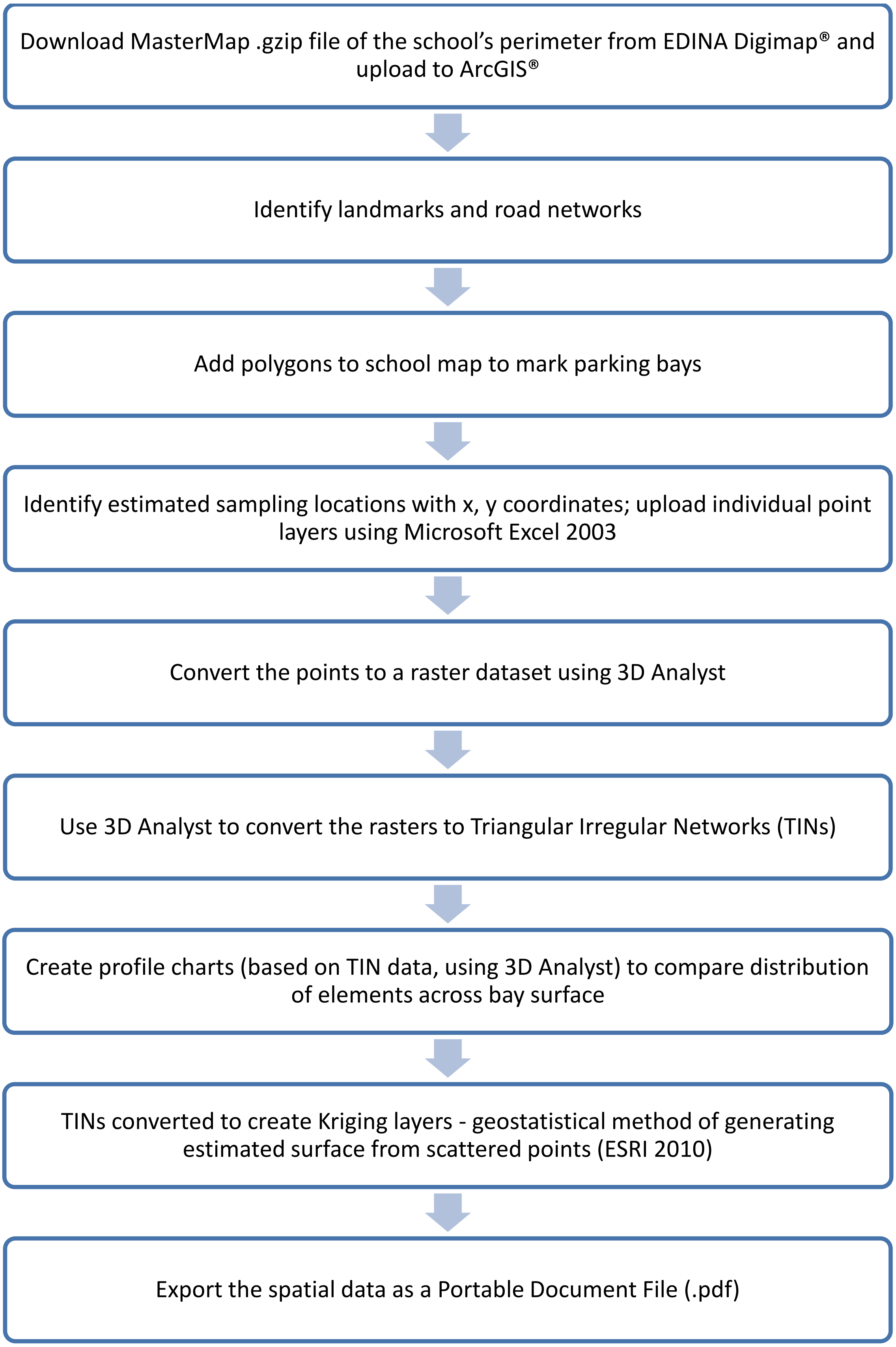

Figure 28 GIS mapping methodology

3.11 Survey of VPS usage by school staff

To determine how the VPS parking bays were being used at Clinton Primary, a survey was designed to assess the users parking habits and their opinions on the VPS. The survey was completed by school staff that drove to work, as they utilised the car park on a regular basis. The questions were designed to determine if the staff used the VPS parking bays instead of the asphalt bays, and reasons if they chose not to. The survey also aimed to determine which bays were favoured more by users and their vehicle movement into the bays (driven forwards or reversed). Understanding parking habits may help to explain areas of pollution identified across the VPS. The respondents of the survey were also requested to give their opinion on VPS, as research on a surface of this nature has not been investigated previously. The full questionnaire can be found in Appendix II.

3.12 Conclusion

To address the aims that were described in the first chapter, this section described the techniques addressing objectives stated in Section 1.9. The results are divided into two chapters which follow. The results of the pot trials are given in Chapter 4, identifying grass species' tolerance of contamination through determination of the Median Effective Concentration (EC_{50}) at which 50% of the biomass growth was inhibited by oil contamination. Chapter 5 focuses on the field trial and the construction of the ArcGIS interactive map using the results generated. Compaction data of the VPS determined whether the whole vegetating parking area was subjected to similar compaction pressures or if this was isolated to certain locations across the surface.

Geochemical and magnetic data provided a means of determining if the parking of cars on a VPS elevated contamination levels of vehicular origin. These techniques offered quick and highly accurate data, highlighting similarities in pollution identification. These data were compared to determine if similar results had been established, and if magnetism techniques could be used for pollutant determination without the need for geochemical analysis.

Chapter 4 Preliminary Pot Trial Results

In the previous chapter, the approach was described to determine the effects of oil contamination on the four chosen grasses which may be utilised in VPSs. The aims and objectives introduced in Chapter 1, Section 1.9 focused Chapter 3 to justify the division of the study into two investigations: pot trials and a larger scale, VPS trial. Comparing results with other pollution studies in Chapter 2, the grass species' suitability for contamination tolerance were assessed. This chapter provides results obtained from a pot trial identifying the impacts on grass growth after oil application, which in conjunction with a parallel pot trial that investigated element concentrations in compost samples and accumulation in grass biomass subsequent to oil contamination (Seel 2006) provided an indication of suitable grass species for an environment subjected to pollutant contamination, addressing the first aim and its objectives. Biomass production and growth inhibition due to increasing amounts of oil contamination were determined through statistical analyses (ANOVA and regression) and determination of EC_{50}, which identified oil volumes that caused 50% growth inhibition in each species (decreasing values signify greater toxicity). Literature in Chapter 2 highlighted pot trials that investigated plant growth reduction as a consequence of contamination, including grass growth after oil spillage and following application of street dust to compost (McGrath 1992; Sharifi, Sadeghi and Akbarpour 2007; Waite 2010), providing possible indications on how the four grass species may respond to contamination. Resulting biomass data from the four grass species was comparable to these investigations in determination of their suitability for VPS.

4.1 Growth of four grass species in oil-contaminated compost

A preliminary pot trial assessed the growth of four grass species in a triple-replicated series of increasing oil concentrations which were applied to compost. To ensure validity of results, positive controls consisting of grass seeds and no oil contamination, and negative controls consisting of each oil concentration but without seeds sown on the compost surface, were included to provide different variables in the trial. Using Microsoft Excel 2007, mean biomass data from grass replicates harvested and dried every 28 days was subjected to Two-Way Analysis of Variance (ANOVA) and regression analyses. Numerous data were extracted from each harvest, thus the full data sets, ANOVA and regression analyses, can be found on the disk at the back of this thesis for reference. This chapter immediately presents statistical analyses of the harvest data located on the disk.

4.1.1 Analysis of Variance between grass species and increasing oil contamination

A Two-Way ANOVA was carried out to determine whether there was an interaction between the grass species and the volume of oil contamination which cause an effect on the amounts of plant biomass produced.

Two-Way ANOVA data (Appendix IB) determined that for each of the harvests, increasing oil concentrations showed significant effects on biomass production. Tables 18 and 19 summarise P-values from Two-Way ANOVA, displaying interaction between biomass production by the grass species and amount of oil contamination present in the compost. Analysing both fresh and dried samples, data determined that grass growth by all four species was significantly affected ($P = <0.05$) through the application of oil.

Table 18 Two-Way ANOVA analyses of wet mean weights (P-value for interaction between oil and grass) (P = 0.05)

Species	Harvest 1	Harvest 2	Harvest 3	Harvest 4	Harvest 5	Harvest 6
A. stolonifera L.	$6.62E^{-15}$	$2.96E^{-13}$	$1.69E^{-07}$	$5.41E^{-10}$	$2.19E^{-11}$	$1.66E^{-21}$
F. rubra L.	$9.84E^{-11}$	$4.38E^{-13}$	$3.91E^{-12}$	$8.76E^{-10}$	0.000194	0.000321
P. trivialis L.	$2.82E^{-09}$	$1.88E^{-10}$	$2.78E^{-10}$	$2.1E^{-08}$	0.021445	0.000178
L. perenne L.	$1.27E^{-19}$	$1.02E^{-17}$	$7.08E^{-18}$	$1.66E^{-16}$	$8.8951E^{-10}$	$3.45E^{-09}$

Table 19 Two-Way ANOVA analyses of dry mean weights (P-value for interaction between oil and grass) (P = 0.05)

Species	Harvest 1	Harvest 2	Harvest 3	Harvest 4	Harvest 5	Harvest 6
A. stolonifera L.	$1.05E^{-13}$	$1.64E^{-12}$	$6.02E^{-07}$	$1.77E^{-09}$	$3.95E^{-09}$	$5.05E^{-23}$
F. rubra L.	0.001	$5.29E^{-13}$	$6.46E^{-13}$	$1.81E^{-09}$	0.00011	0.000235
P. trivialis L.	$9.12E^{-10}$	$4.3E^{-11}$	$4.31E^{-10}$	$3.85E^{-11}$	0.016601	0.000451
L. perenne L.	$1.68E^{-17}$	$1.84E^{-17}$	$1.81E^{-16}$	$2.16E^{-08}$	$1.2E^{-08}$	$6.05E^{-08}$

4.1.2 Regression analysis between grass species and oil contamination

Harvest data from the pots was also subjected to regression analysis to determine the relationship between oil contamination and the individual grass species. Figure 29 displays regression charts for fresh grass biomass sampled at Harvest 1, with Tables 20 and 21 showing a summary of R values for the four species at each harvest. Full regression data and analysis charts are located in Appendix IC. Analysing both fresh and dried samples, data determined that grass growth by all four species was significantly affected through the application of oil. The majority of samples indicated that there was a negative relationship between the amounts of plant biomass produced with the increase in oil contamination.

Data produced from Harvest 6 samples showed that there was little, if any, relationship between the biomass produced and the oil contamination volume.

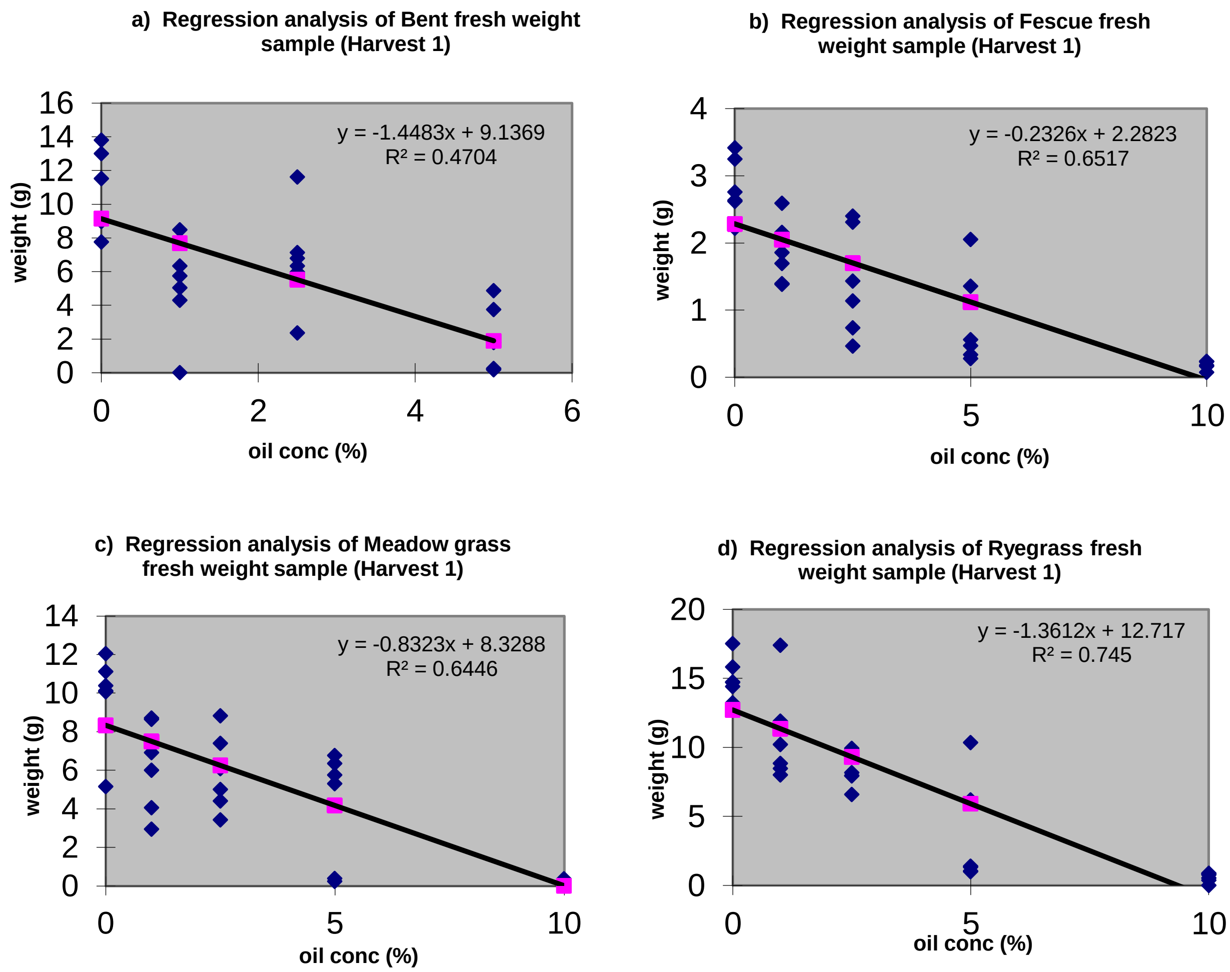

Figure 29 Regression analysis of fresh grass biomass samples (Harvest 1)

Table 20 Regression summary of the effect of oil on four grass species (fresh samples)

Species	Harvest 1	Harvest 2	Harvest 3	Harvest 4	Harvest 5	Harvest 6
A. stolonifera L.	0.4704	0.5116	0.4133	0.2566	0.095	0.3263
F. rubra L.	0.6517	0.6967	0.5799	0.4387	0.3	0.0931
P. trivialis L.	0.6446	0.227	0.5143	0.3167	0.0463	0.0478
L. perenne L.	0.745	0.7318	0.5614	0.371	0.5559	0.0069

Table 21 Regression summary of the effect of oil on four grass species (dry samples)

Species	Harvest 1	Harvest 2	Harvest 3	Harvest 4	Harvest 5	Harvest 6
A. stolonifera L.	1	0.5217	0.4293	0.3619	0.0507	0.3504
F. rubra L.	0.6161	0.7348	0.5839	0.4578	0.2883	0.0801
P. trivialis L.	0.6827	0.209	0.5224	0.371	0.0656	$2E^{-06}$
L. perenne L.	0.7494	0.7275	0.6235	0.4554	0.5626	0.002

4.2 Cumulative weight produced by the grasses

Measuring the cumulative weight of each species during the pot trial determined which grass(es) exhibited most growth despite the presence of oil contamination. Appendix ID displays cumulative wet weight tables for each of the grass species during the pot trial. Fresh biomass weights were used to determine most cumulative growth; noting freshly harvested weights prior to subjecting the plant material to drying and additional preparation (e.g. homogenisation), maintained consistency in the methodology. *F. rubra* L. produced least total cumulative growth, whereas *L. perenne* L. (with the exception of Harvest 5 where *P. trivialis* L. is greater, which supports the insignificant regression results) showed the greatest total cumulative growth in each of the oil contamination volumes. Most growth for each species occurred in pots without oil contamination (0% (w/v) i.e. the positive control), with least growth at 10% (w/v) and no growth at 20% (w/v). Figures 30-33 show the cumulative growth of each individual species during the trial. The cumulative biomass growth charts show greatest growth for each species in oil concentrations of 0% to 5% (w/v) and during the first two months of the trial, before growth plateau. Growth of each species in oil concentration of 10% (w/v) was slow to accumulate, increasing in Harvests 5 and 6, with least cumulative growth (if any) in 20% (w/v) oil contamination

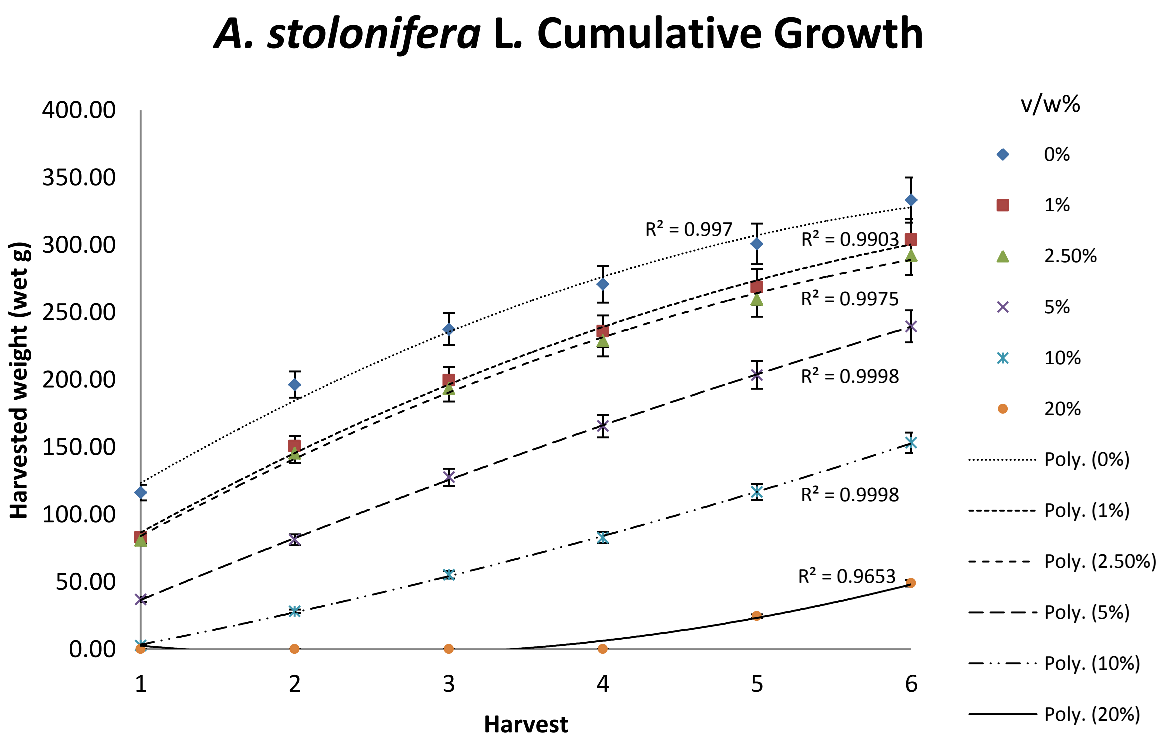

Figure 30 Cumulative *A. stolonifera* L. Growth

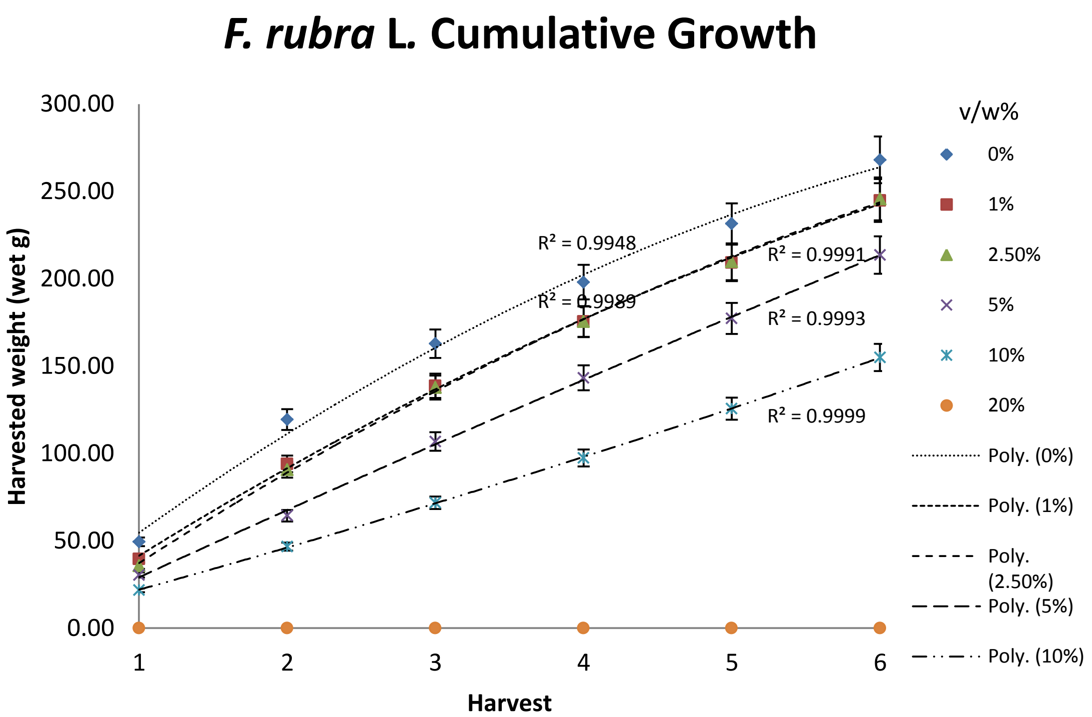

Figure 31 Cumulative *F. rubra* L. Growth

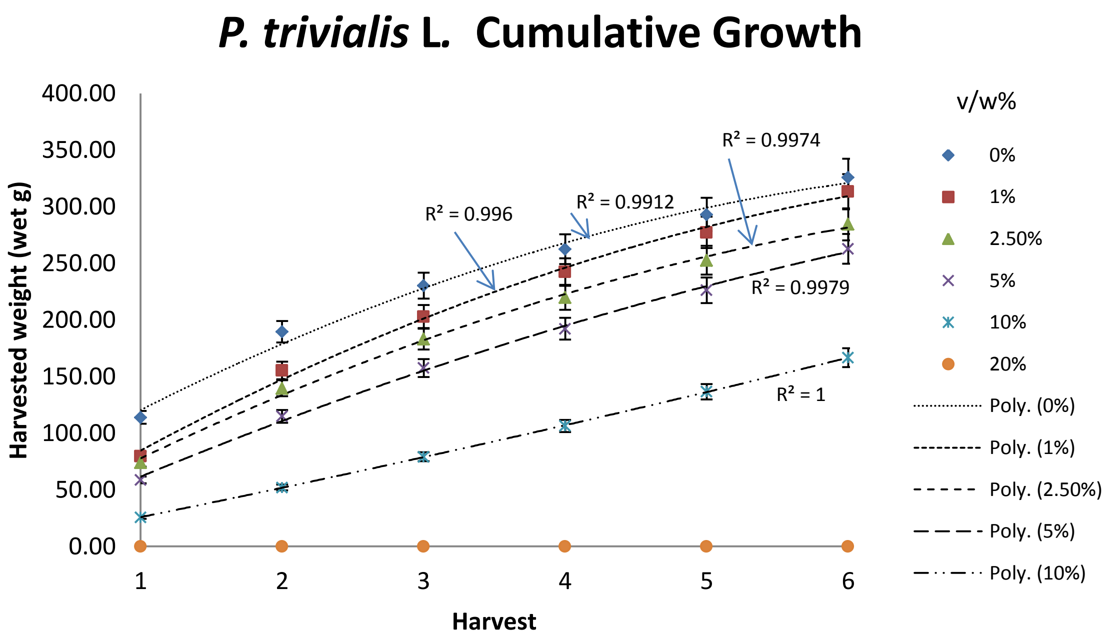

Figure 32 Cumulative *P. trivialis* L. Growth

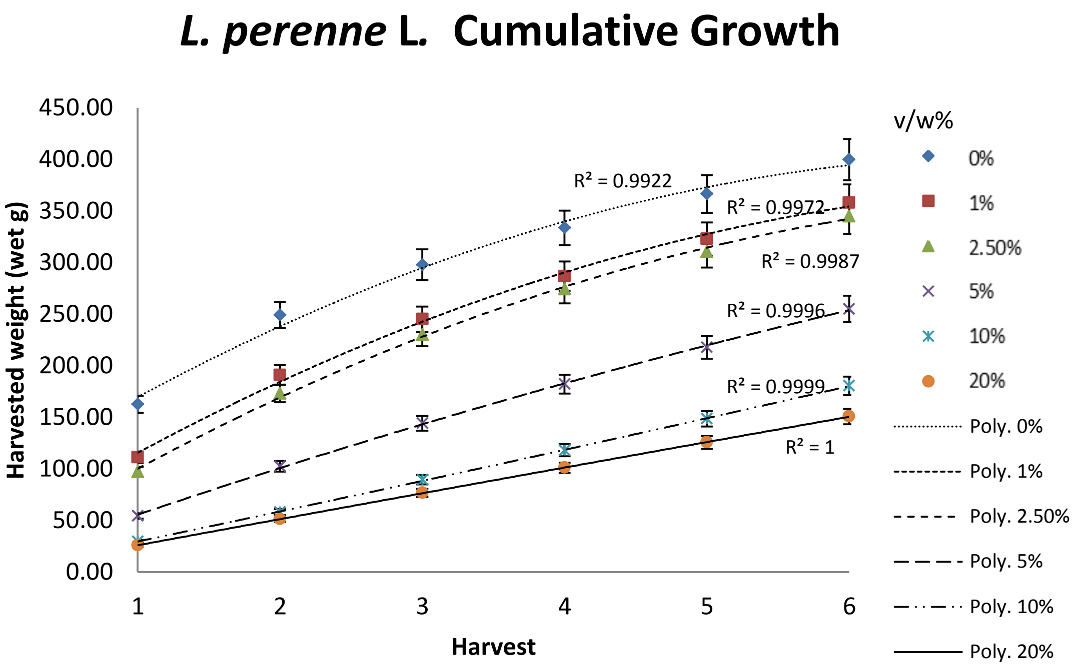

Figure 33 Cumulative *L. perenne* L. Growth

4.4 Determining EC_{50} for 50% effective concentration

EC_{50} values for the four grass species in Harvest 1 were determined, as there was only one application of oil to the pots, which was at the start of the experiment. Without additional applications of oil to the pots at later stages of the trial, contamination levels in the compost would decline, either washing through the compost or through degradation. Measuring EC_{50} values later on in the study without additional oil applications would not provide accurate growth inhibition results, thus Harvest 1 data is considered here.

Table 22 and Figure 34 show the volumes of oil required to prevent half of the growth for the grass species. Decreasing volumes identified greater toxicity, thus the greater the volume of oil required to inhibit 50% of growth, the greater the tolerance of contamination.

Table 22 EC_{50} growth inhibition summary of the effect of oil contamination on four grass species

Species	Approximate Oil Amount Required for EC_{50} in Fresh Samples (%)	Approximate Oil Volume Required for EC_{50} in Fresh Samples (ml)
Agrostis stolonifera L.	5.3	13.25
Festuca rubra L.	8.5	21.25
Poa trivialis L.	6.6	16.5
Lolium perenne L.	6.2	15.5

Referring to Table 22, *F. rubra* L. required the greatest volume of oil to inhibit 50% of growth (21.25ml) and *A. stolonifera* L. needed the least volume (13.25 ml). *P. trivialis* L. had an EC_{50} value which were slightly greater than *L. perenne* L., indicating both species had less tolerance of oil contamination.

Briefly summarising the data observed, all species inhibited growth had a significant relationship with the increase in oil contamination in the compost; *L. perenne* L. had the greatest cumulative growth over six months and *F. rubra* L. showed the most tolerance of oil contamination in the compost as more was required to suppress 50% of its growth.

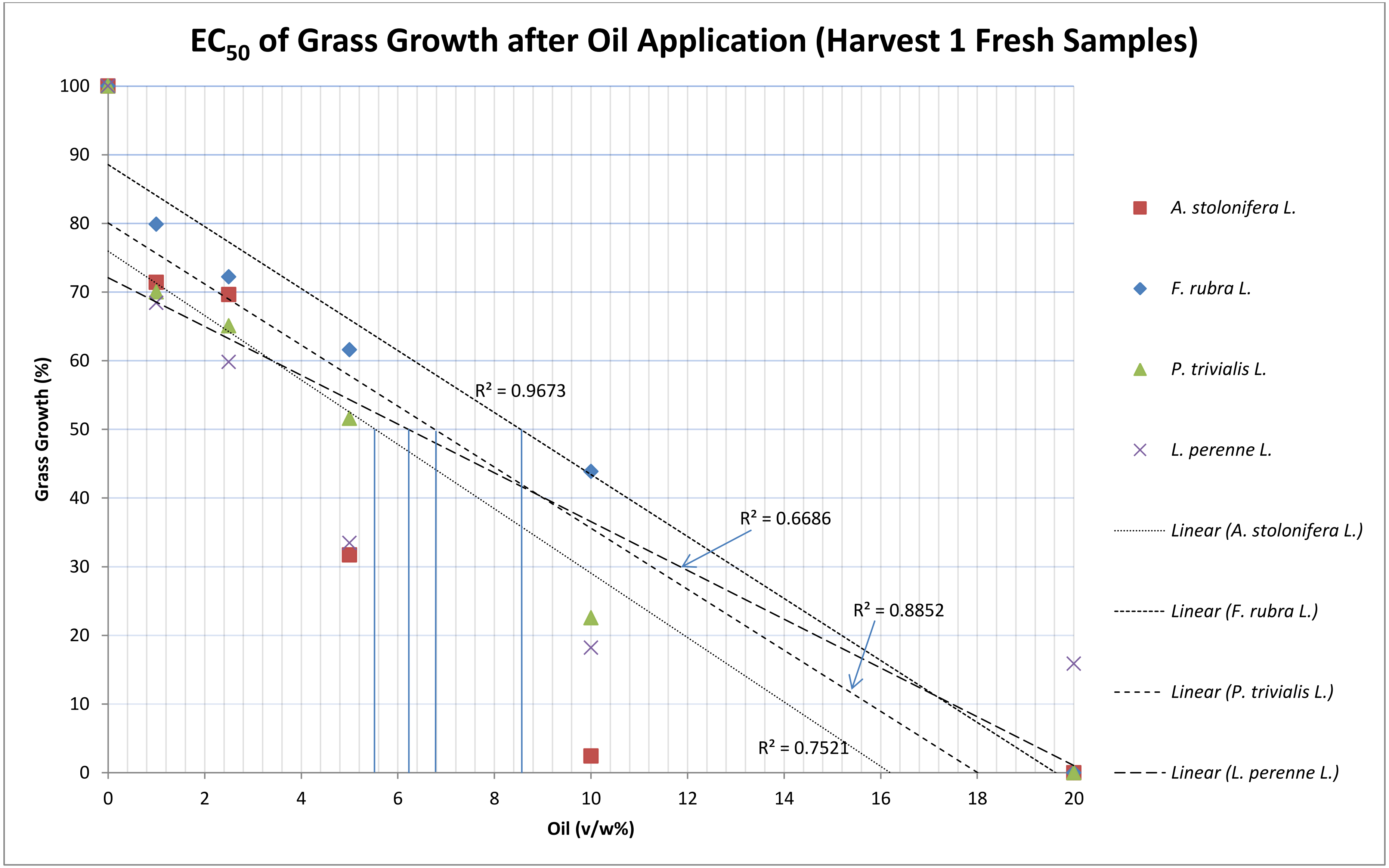

Figure 34 EC_{50} of Grass Growth after Oil Application (Harvest 1 fresh samples)

4.5 Heavy metal distribution in plants and compost

Providing supplementary data alongside the pot trial for growth assessment, an additional pot trial was conducted, to assess pollutant accumulation in grass and compost samples. Using the same experimental design as the growth assessment trial, four grass species were subjected to increasing oil concentrations and samples were harvested every 28 days over a 3-month period. Upon conclusion of analysis, the data obtained from the samples was subjected to two-way ANOVA to determine how significant the effects of oil and grass type were on the accumulation and content of the elements analysed. Full data for this additional pot trial can be found on the 'Additional Appendices' disk at the back of this thesis. Tables 23 and 24 display a summary of resulting P-values following analysis of the element content in compost and grass respectively.

General observations by Seel (2006) indicated that Al, Ca, Cr, K, Mo and P concentrations initially increased following application and decreased afterwards; the concentration of Mg followed a decreasing trend as oil contamination increased; and Cu, Pb and Zn had concentrations of normal compost levels or lower.

4.5.1 ANOVA of Element Contamination in John Innes Compost

ANOVA was employed to determine how grass species and compost factors affected element concentrations following application of oil to the compost, and if both factors interacted with each other to influence the concentrations. Referring to Table 23, the interaction of the grass species with the presence of oil contamination had no significant influence on the element concentrations in the compost, with the exception of Cu at Harvest 3 ($P = 0.01$). Mean concentration differences of Ca, K and Mo were shown to be significantly influenced by compost but this was not apparent until Harvests 2 and 3. The presence of different grass species had significant effect on mean element concentrations in the compost, but this did not occur until Harvests 2 and 3 in most samples.

4.5.2 Element Accumulation in Four Grass Species

ANOVA was also applied to grass biomass data, to determine whether the species, the compost and the interaction of both factors influenced the accumulation of elements in the grass material. Table 24 highlights seven elements at Harvest 1 where the mean concentration in plant material was significantly affected by the interaction of both grass species and compost, following oil application. Data for Al (P = 0.31), Cr (P = 0.68) and Pb (P = 0.15) showed no significance in element accumulation at Harvest 1. None of the elements were significantly influenced by grass/compost interactions at Harvest 2, and only Mg and Mo concentrations showed grass/compost interaction significance at Harvest 3. Both studies indicated that overall, the presence of oil contamination did not have a significant effect of element concentrations in compost and in plant accumulation.

Table 22 P-Value Summary Table from Compost Samples (highlighted cells indicate significance influence on element concentration)

	Aluminium			Calcium			
P-Value	**Harvest 1**	**Harvest 2**	**Harvest 3**	**P-Value**	**Harvest 1**	**Harvest 2**	**Harvest 3**
Effect of compost	0.98	0.29	0.29	**Effect of compost**	0.06	0.27	**0.02**
Effect of grass species	0.62	**0.00**	**0.00**	**Effect of grass species**	0.74	**0.01**	**0.01**
Interaction	0.91	0.31	0.14	**Interaction**	0.94	0.84	0.20
	Chromium			**Copper**			
P-Value	**Harvest 1**	**Harvest 2**	**Harvest 3**	**P-Value**	**Harvest 1**	**Harvest 2**	**Harvest 3**
Effect of compost	0.05	0.43	0.43	**Effect of compost**	0.35	0.44	0.28
Effect of grass species	0.12	0.43	**0.02**	**Effect of grass species**	0.81	0.43	**0.00**
Interaction	0.66	0.50	0.43	**Interaction**	0.91	0.49	**0.01**
	Potassium			**Magnesium**			
P-Value	**Harvest 1**	**Harvest 2**	**Harvest 3**	**P-Value**	**Harvest 1**	**Harvest 2**	**Harvest 3**
Effect of compost	0.38	**0.04**	0.19	**Effect of compost**	0.13	0.44	0.28
Effect of grass species	0.36	**0.00**	0.17	**Effect of grass species**	0.52	**0.00**	**0.00**
Interaction	0.89	0.10	0.43	**Interaction**	0.96	0.32	0.10
	Molybdenum			**Phosphorus**			
P-Value	**Harvest 1**	**Harvest 2**	**Harvest 3**	**P-Value**	**Harvest 1**	**Harvest 2**	**Harvest 3**
Effect of compost	0.31	0.44	**0.01**	**Effect of compost**	0.63	0.34	0.30
Effect of grass species	0.31	0.43	0.17	**Effect of grass species**	0.74	**0.00**	**0.01**
Interaction	0.83	0.49	0.57	**Interaction**	0.77	0.43	0.12
	Lead			**Zinc**			
P-Value	**Harvest 1**	**Harvest 2**	**Harvest 3**	**P-Value**	**Harvest 1**	**Harvest 2**	**Harvest 3**
Effect of compost	0.29	2.97	0.37	**Effect of compost**	0.23	0.12	0.45
Effect of grass species	0.97	1.47	**0.02**	**Effect of grass species**	0.35	**0.00**	0.36
Interaction	0.97	1.09	0.15	**Interaction**	0.64	0.07	0.48

Table 23 P-Value Summary Table from Grass Samples (highlighted cells indicate significance influence on element concentration)

	Aluminium			Calcium			
P-Value	**Harvest 1**	**Harvest 2**	**Harvest 3**	**P-Value**	**Harvest 1**	**Harvest 2**	**Harvest 3**
Effect of compost	0.10	**0.00**	**0.00**	**Effect of compost**	**0.00**	**0.00**	**0.00**
Effect of grass species	0.06	0.25	0.25	**Effect of grass species**	**0.00**	0.14	**0.01**
Interaction	0.31	0.62	0.62	**Interaction**	**0.00**	0.64	0.07
	Chromium			**Copper**			
P-Value	**Harvest 1**	**Harvest 2**	**Harvest 3**	**P-Value**	**Harvest 1**	**Harvest 2**	**Harvest 3**
Effect of compost	0.33	**0.00**	**0.00**	**Effect of compost**	**0.00**	**0.00**	**0.00**
Effect of grass species	0.56	**0.00**	0.09	**Effect of grass species**	**0.00**	**0.01**	0.65
Interaction	0.68	0.07	0.48	**Interaction**	**0.00**	0.11	0.07
	Potassium			**Magnesium**			
P-Value	**Harvest 1**	**Harvest 2**	**Harvest 3**	**P-Value**	**Harvest 1**	**Harvest 2**	**Harvest 3**
Effect of compost	**0.00**	**0.00**	**0.00**	**Effect of compost**	**0.00**	**0.00**	**0.00**
Effect of grass species	**0.00**	0.15	**0.01**	**Effect of grass species**	**0.00**	0.13	**0.00**
Interaction	**0.00**	0.41	0.14	**Interaction**	**0.00**	0.62	**0.02**
	Molybdenum			**Phosphorus**			
P-Value	**Harvest 1**	**Harvest 2**	**Harvest 3**	**P-Value**	**Harvest 1**	**Harvest 2**	**Harvest 3**
Effect of compost	**0.00**	**0.00**	**0.00**	**Effect of compost**	**0.00**	**0.00**	**0.00**
Effect of grass species	**0.00**	**0.03**	**0.00**	**Effect of grass species**	**0.00**	0.55	**0.00**
Interaction	**0.00**	0.16	**0.03**	**Interaction**	**0.00**	0.55	0.10
	Lead			**Zinc**			
P-Value	**Harvest 1**	**Harvest 2**	**Harvest 3**	**P-Value**	**Harvest 1**	**Harvest 2**	**Harvest 3**
Effect of compost	0.09	n/a	**0.00**	**Effect of compost**	**0.00**	**0.00**	**0.00**
Effect of grass species	**0.00**	n/a	**0.02**	**Effect of grass species**	**0.00**	**0.04**	**0.02**
Interaction	0.15	n/a	0.33	**Interaction**	**0.00**	0.42	0.33

4.6 Overview of Pot Trial Results

A pot trial monitored effects of used vehicle engine oil on the growth of four grass species: *A. stolonifera* L., *F. rubra* L., *L. perenne* L. and *P. trivialis* L. These species were utilised as model systems to reflect grasses which had been identified to provide low maintenance surface coverage, durability and erosion control in other vegetative surfaces (for example, waterway design (Hewlett, Boorman and Bramley 1987)). This led to the assessment of whether they could sufficiently resist the presence of oil following application to their growing medium (in the case of this study, John Innes compost), promoting additional understanding of these species' characteristics (see Section 2.2) and whether they could be utilised in the surface coverage of a VPS. Previous work on VPSs is limited in comparison to the amount of work that has been performed on other vegetative SUDS, heavy metals and other vehicular contaminants in relation to their effect on plants, so the information obtained from this work will form the platform for further study.

As *A. stolonifera* L., *F. rubra* L., *L. perenne* L. and *P. trivialis* L. grew in the oil-contaminated compost, it was observed that the presence of the contaminant repressed growth, the effect intensifying as the percentage of the contamination increased. ANOVA and regression analyses provided probability and R^2 values respectively (Tables 18-21), proving the theory that an increase of oil contamination in the compost initiated a decline in grass biomass production. Growth that did take place in some pots at increased oil concentrations (10% and 20%) did not produce sufficient plant material for examination that could allow significant data analysis. This may be due to the direct effect of the oil on the grasses or some indirect effect, for example the reduction in the amount of water reaching the plant roots, if the oil acted as a repellent.

Research by McGrath (1992) subjected *L. perenne* L. *cv*. Vigor to increasing volumes of diesel oil in soil mixtures, investigating the oil volume required for ED_{50} and the reduction in growth over a two-year experimental period. Similarly to this research, McGrath (1992) demonstrated that germination and growth of *L. perenne* L. *cv*. Vigor occurred at lower rates of contamination, and was inhibited by greater oil contamination volumes. Scaling up the study to field trial size, McGrath (1992) simulated leaks of increasing oil concentrations (0.5 g to 16 g oil/ 100 g soil) on a vegetative surface consisting of *L. multiflorum cv*. Meritra and investigated sward death and alteration in levels of carbon content. Following initial vegetation destruction, further growth demonstrated no significant excess C content in sampling. McGrath suggested biodegradation, leaching or evaporation as likely consequences of C content control. This suggests that vegetation demonstrates suitable pollutant control, making it suitable for use in VPS. In a similar study, *Panicum virgatum, Festuca arundinacea* and *Cajanus cajan* were subjected to growth in oil-contaminated soil and demonstrated that it was possible for plants to endure this pollution, even if growth was affected (Vavrek and Campbell, 1999). With the majority of grass growth below 5% oil contamination in this research, it has been found that *A. stolonifera* L., *F. rubra* L., *L. perenne* L. and *P. trivialis* L. have partial tolerance to oil-contaminated compost, making any growth above this oil contamination concentration more or less unfeasible. Statistical analysis showed that the presence of oil had a significantly negative effect on growth as oil concentrations increased.

Information on the effects of used vehicle engine oil on growth of four grass species was supplemented by an additional investigation on the accumulation of elements in grass biomass and element concentrations detected in compost (Seel 2006). Analysing elements based on a study on used vehicle oil contaminants (Coupe *et al*. 2005), Seel (2006) detected Ca, Cu, K, Mg, Mo, P and Zn were significantly influenced by the interaction between the grass species and compost at the first harvest. However, these significant effects were only shown again in Mg and Mo at Harvest 3. Independently, compost seemed to influence element concentration in grass samples, and grass species had some influence in element concentrations in Harvest 2 and 3 samples (see Table 24). Compost samples indicated no significant element concentration influence between the interaction between the grass species and oil presence, with the exception of Cu in samples obtained during Harvest 3. Independently influencing Ca, K and Mo concentrations, samples from Harvests 2 and 3 identified that these element concentrations were significantly affected by compost. Grass species displayed more independent influence on element concentrations, as shown in Table 24.

Table 25 Soil guideline values, indicating background, trigger and action values (based on ICRCL (1987) and Environment Agency Guidelines (2009))

	As	Cd	Cr	Cu	Hg	Pb	Se	Ni	Zn
Background	32	0.62	15	25.8	1	29.2	3.25	33.7	59.8
CLEA values	nd	30	100	nd	26	450	40.6	75	nd
ICRCL trigger values	10-40	3-15	600-1000	130	1-20	500-2 000	3-6	70	300
ICRCL action values	40	15	1000	423	20	813	6	376	1665

Table 25 summarises soil guideline values for heavy metal concentrations, which support the assessment of risk to health from exposure to contamination in soil. Data indicates background levels which are tolerable (or pose minimal risk) to human health, trigger values at which levels may pose significant harm to health, and action values at which concentrations pose unacceptable risks to health or the environment thus require attention.

Concentrations detected by Seel (2006) determined that elements accumulated in grass biomass and compost samples did not exceed guideline trigger values. Full data is located in Additional Appendices on the disk at the back of this thesis. From these results, Seel (2006) concluded that overall, the presence of oil following application to compost did not have a significant effect of mean element concentration in grass and compost samples. Waite (2010) also identified gradual increases in grass shoot element concentration, notably Cu, Pb and Zn, as street dust contamination increased. Analysing samples with ANOVA, neither the grass species nor street dust independently influenced element concentrations in grass shoot, highlighting significant interaction between both species and street dust. Similarly to Seel (2006), Waite (2010) identified that using ANOVA, element concentrations in compost did not significantly differ despite increasing street dust applications.

Both these studies identify that element concentrations altered in grass samples following growth in contaminated compost, despite concentrations not displaying significant changes in the compost itself. This information suggests that a VPS may tolerate element contamination resulting from vehicle wear and tear (i.e. rusting, brake abrasion, tyre deterioration) and exhaust emissions; further investigation on element concentration in VPS grasses could form a subsequent study.

Overall this project has shown statistically that oil has an effect on *Agrostis stolonifera* L., *Festuca rubra* L., *Lolium perenne* L. and *Poa trivialis* L., showing changes in biomass production in the pot trial and in element concentration accumulation in the associated pot trial by Seel (2006). It was therefore concluded that the presence of oil in compost promoted change in plant tissue, whether it be physical (decrease in biomass production) or the internal change in element composition. Taking into account all of the data obtained from the experiment, it can be seen that further analysis on each aspect of this research could lead to strong conclusive results on the effect of the presence of oil on different grass species, and certainly on their oil retention capabilities of VPSs. Further investigation into VPSs would be required to provide the resulting outcome.

Chapter 5 Results from the Field Trial

5.1 Introduction

Chapter 4 described the grass biomass production data resulting from the application of vehicle oil, and compared pollution content in the grasses and compost with studies highlighted in Chapter 2. Determining effects of growth inhibition and pollution uptake by the presence of oil on the four grasses formed a fundamental part in the design and function of VPS by identifying species whose characteristics tolerate contamination and perform pollution control. Previous studies (Vavrek and Campbell 2002; Dominguez-Rosado and Pichtel 2004; Vwioko and Fashemi 2005; Tanushree *et al*. 2011; Mmolawa, Likuku and Gaboutloeloe 2011) on pollution in vegetated locations investigated large scale areas which were subjected to anthropogenic pollution. To explore the effect of vehicles on a smaller scale vegetative surface, samples obtained from a regularly used VPS were analysed to determine the distribution of heavy metals and magnetic properties. In conjunction with responses from the questionnaires on VPS bay usage, these data would expose whether frequency of parking would influence compaction and contamination rates.

Principle component analysis (PCA) cluster charts and dendrograms identified the components that emphasised the majority of variance from the samples and their interactions. Boxplots identified compaction and geochemical data relationships between the six sampling areas. The relationship between low frequency susceptibility (χlf) and elemental concentrations, and between saturated isothermal remanent magnetism (SIRM) and low frequency susceptibility (χlf), identified whether magnetism data could be used to indicate elemental pollution. The final component to this chapter, which makes the research unique, presents compaction and element contamination data in an interactive map. The interactive capabilities of the map enable the data, stored as map layers, to be switched on and off, in order for visual comparisons to be made. Data represented on a map is more visually descriptive than tabulated data, making information understandable to non-GIS users.

5.2 PCA and Cluster Analysis of the VPS

Compaction, geochemical and mineral magnetism data were subjected to Principal Component Analysis (PCA), using PASW Statistics 17, to determine if samples from the non-parked section of the VPS differed in variance to the bays used for regular parking (see Chapter 3.5.2, Figure 22). Summarised in Table 26, PCA exposed several of components with Eigenvalues >1.0 per parking bay, displaying component variance for each sampling location. Screeplots resulting from PCA (Figure 35) identified a clear distinction between the second and third components for each sampling location, thus the first two component loadings for each parking bay were plotted in cluster maps (Figures 36-41).

PCA cluster charts for Bays 1-4 displayed similar groups of samples clustered together, which were similar to the chart produced by the non-parked (control) samples. For each set of data, it was possible to distinguish clusters representing geochemical/heavy metal factors (highlighted in red) and magnetism (highlighted in blue). Cluster charts of VPS samples indicated that some variables were located in the negative axes (latent variables). Although these variables were identified as part of Factor 1 (control and Bay 1-4 samples; Factor 2 for Bay 5 samples), they were not directly observed and were a part of the factor due to their

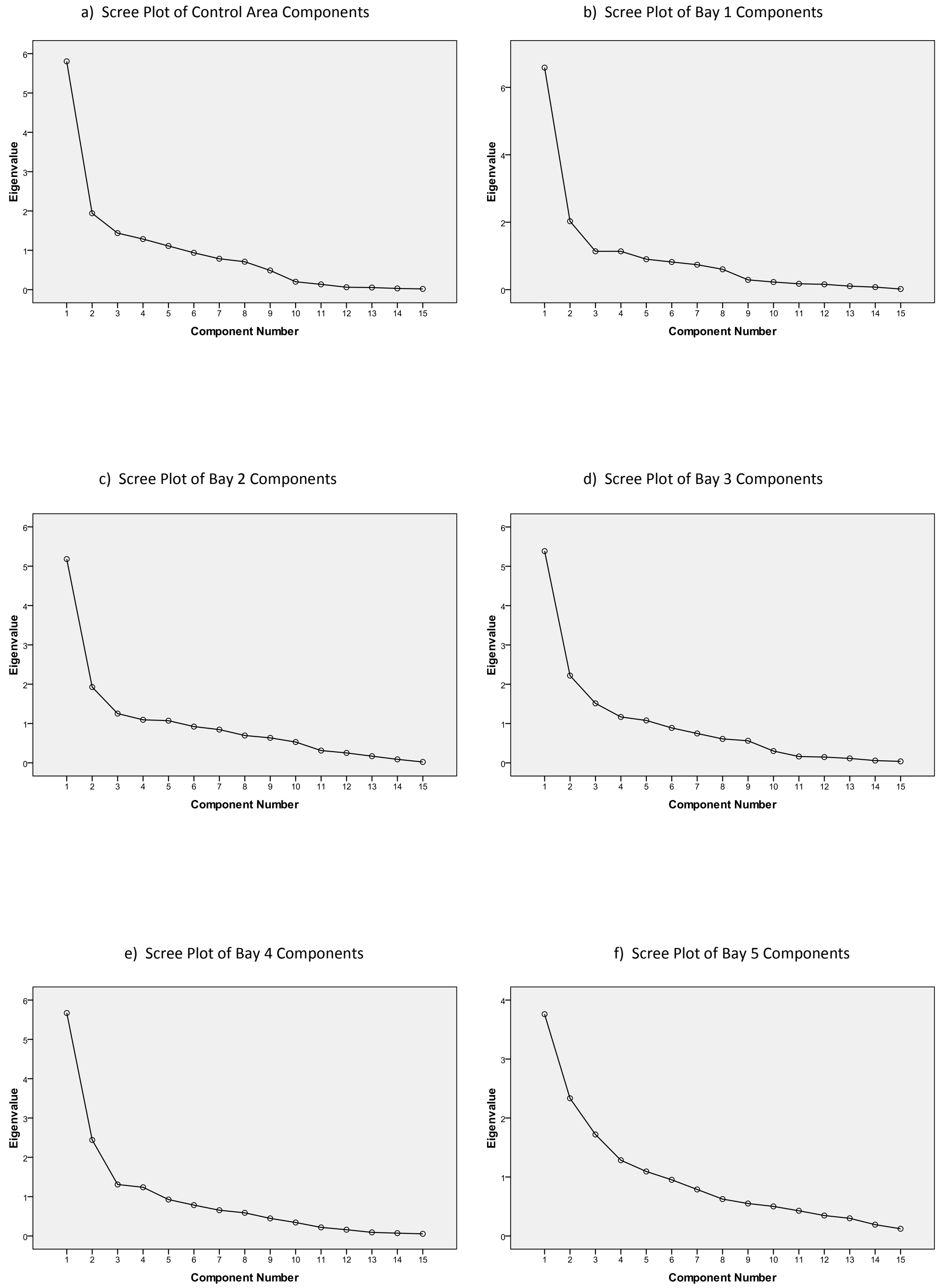

Figure 35 Scree Plots resulting from PCA

common features. A third, smaller cluster (purple) contained the variables for compaction and bulk density, with single factors (mainly

Table 26 Total Variance of Extracted Factors

Control / Outer Area	Rotation Sums of Squared Loadings			
Component	**Total**	**% of variance**	**Cumulative %**	**Variable**
1	5.489	32.288	32.288	Geochemical
2	3.002	17.656	49.944	Magnetism
3	2.279	13.405	63.349	Compaction
4	1.276	7.506	70.856	Ca
5	1.201	7.062	77.917	Mo
6	1.138	6.695	84.612	Cu
Bay 1	**Rotation Sums of Squared Loadings**			
Component	**Total**	**% of variance**	**Cumulative %**	**Variable**
1	6.429	37.819	37.819	Geochemical
2	3.046	17.920	55.739	Magnetism
3	2.024	11.908	67.646	Compaction
4	1.142	6.720	74.366	Mo
5	1.127	6.632	80.998	HIRM
Bay 2	**Rotation Sums of Squared Loadings**			
Component	**Total**	**% of variance**	**Cumulative %**	**Variable**
1	5.009	29.468	29.468	Geochemical
2	3.135	18.441	47.908	Magnetism
3	2.025	11.914	59.822	Compaction
4	1.188	6.990	66.812	Mo
5	1.069	6.286	73.097	Mix (Xfd, Ca)
Bay 3	**Rotation Sums of Squared Loadings**			
Component	**Total**	**% of variance**	**Cumulative %**	**Variable**
1	4.083	24.015	24.015	Geochemical
2	2.990	17.588	41.603	Magnetism
3	2.671	15.714	57.316	Geochemical
4	2.084	12.260	69.576	Compaction
5	1.240	7.293	76.870	Mix (HIRM, Ca)
Bay 4	**Rotation Sums of Squared Loadings**			
Component	**Total**	**% of variance**	**Cumulative %**	**Variable**
1	5.397	31.745	31.745	Geochemical
2	3.187	18.746	50.491	Magnetism
3	2.049	12.055	62.546	Compaction
4	1.283	7.547	70.092	Geochemical
5	1.235	7.265	77.358	Mix (Xfd, K)
Bay 5	**Rotation Sums of Squared Loadings**			
Component	**Total**	**% of variance**	**Cumulative %**	**Variable**
1	3.032	17.836	17.836	Magnetism
2	2.802	16.484	34.320	Geochemical
3	2.287	13.450	47.770	Mix (Compaction, HIRM)
4	1.450	8.531	56.301	Geochemical
5	1.430	8.415	64.715	Geochemical
6	1.400	8.237	72.953	Geochemical

geochemical variables) located in proximity with the geochemical cluster (annotated on the charts or highlighted in green). In comparison to the other sampling locations, the PCA cluster chart for Bay 5 displayed dissimilar components. The magnetism cluster displayed more variance and greater overlap with the geochemical/heavy metal cluster.

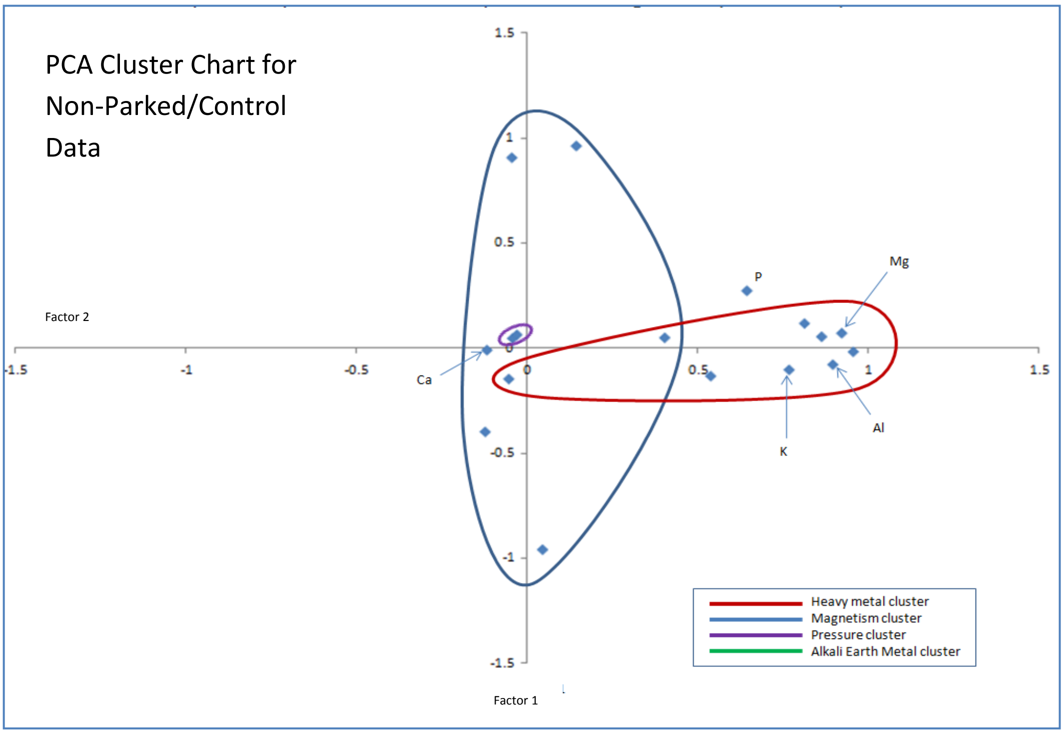

Figure 36 PCA cluster chart of the Non-Parked Area/Control

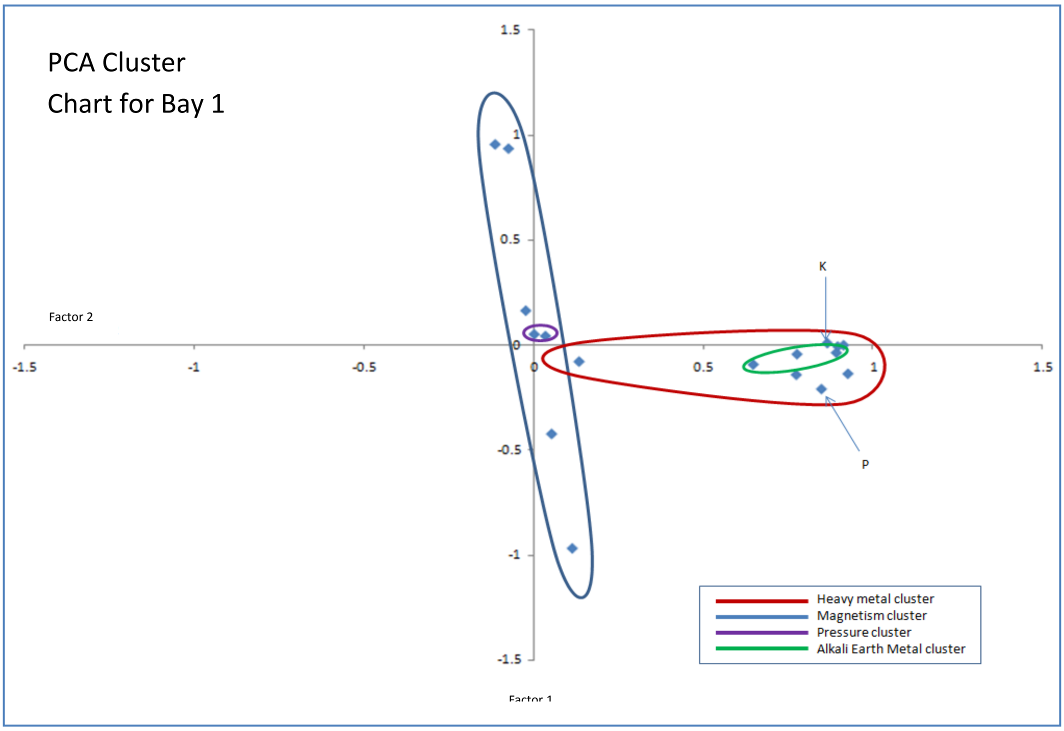

Figure 37 PCA cluster chart of Bay 1

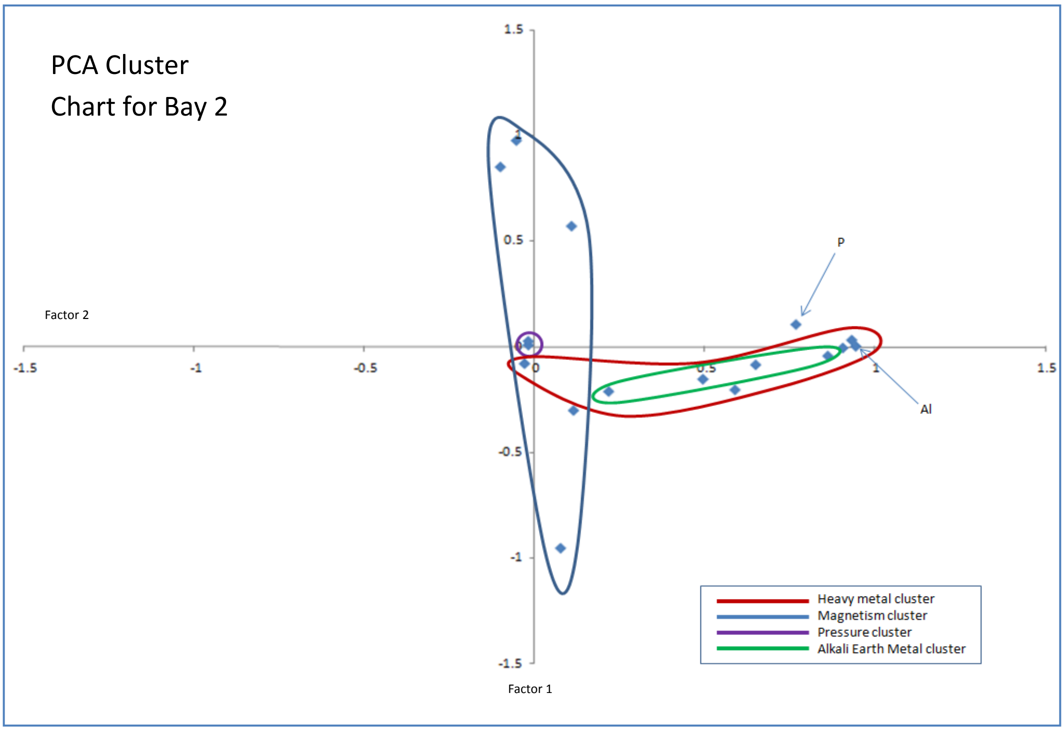

Figure 38 PCA cluster chart of Bay 2

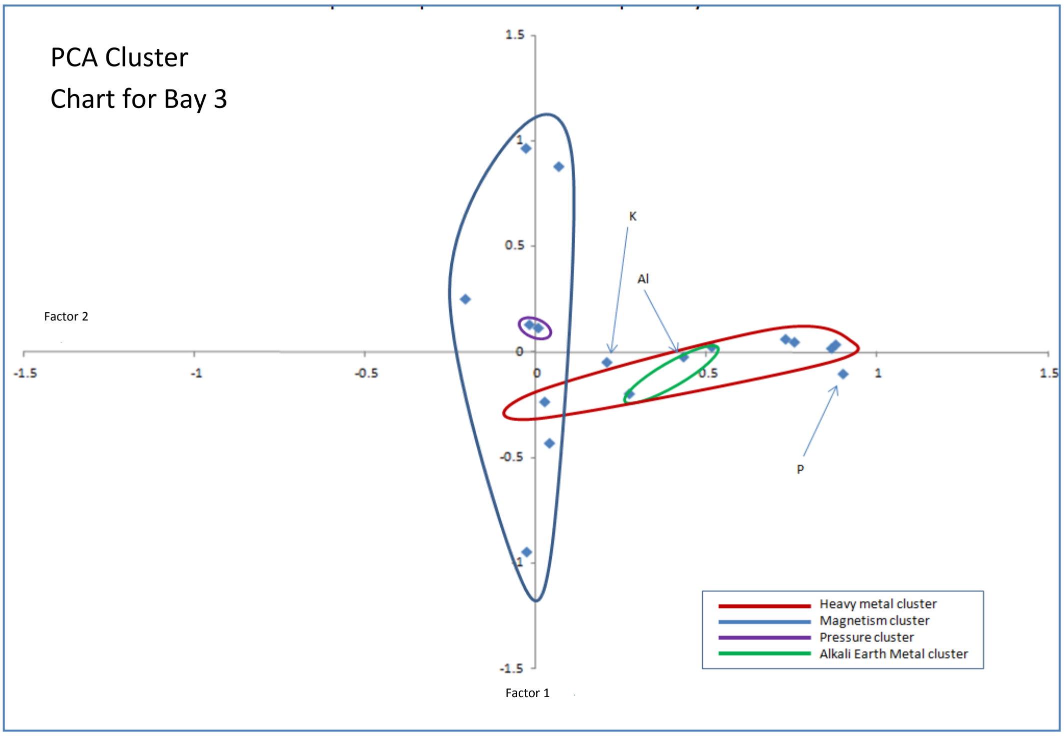

Figure 39 PCA cluster chart of Bay 3

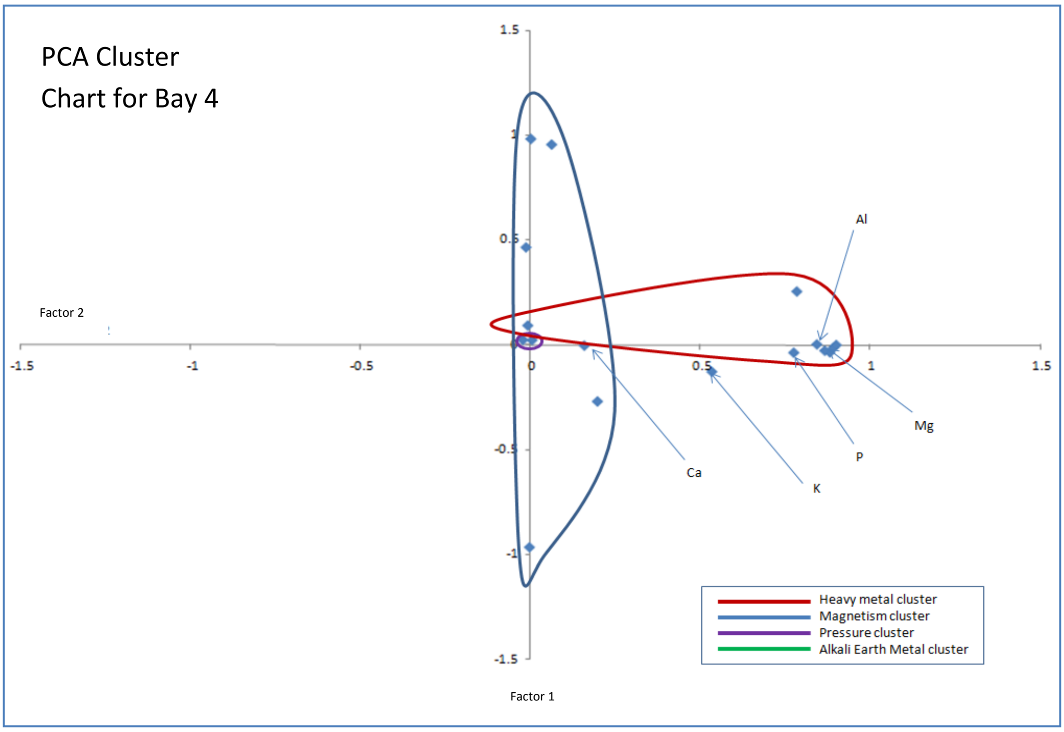

Figure 40 PCA cluster chart of Bay 4

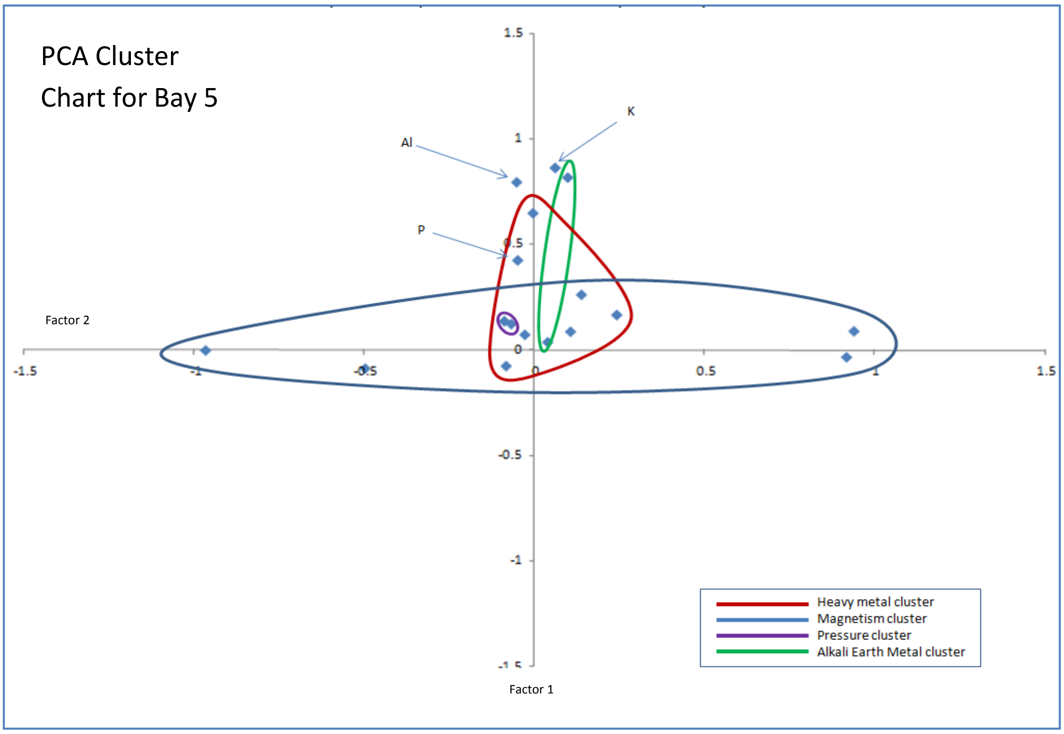

Figure 41 PCA cluster chart of Bay 5

Despite the clear distinction between the magnetism and geochemical clusters, it was not possible to state if there was a significant relationship between geochemical/heavy metals and magnetism components as the clusters overlapped (with the exception of Bay 1).

For clearer understanding of the proximity of the factors in VPS clusters, data was also presented in dendrograms (Figures 42-47). Similarly to the cluster charts, each dendrogram displayed two main clusters, within which the variables were separated into smaller clusters of similarity. With many factors defined within these two clusters, the dendrograms determined that the majority of the geochemical variable means were similar to each other, and mineral magnetism variables were alike. One element which presented dissimilar means to the remainder of the geochemical variables was Mo. For each sampling area, Mo clustered with the mineral magnetism variables. Possibly due to its low concentrations in soil, Mo may lie in this cluster due to its adsorption to iron oxide particles (Wichard *et al*. 2008), which would have been detected by mineral magnetism.

Dendrograms have also shown that alkali earth metals were not always located in the same main cluster. Including the non-parked, control area and Bays 3 and 4, Ca clustered with the mineral magnetism variables, meaning that the mean values were dissimilar to Mg data from these sampling locations. Hendrick and Newlands' (1923) study of soil types stated that mineralogical analysis could be used to determine soil constitution. Identifying that Ca

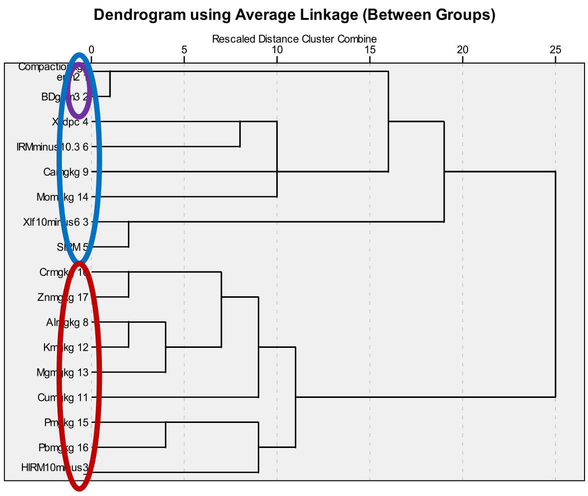

Figure 42 Dendrogram of non-parked/Control Clusters

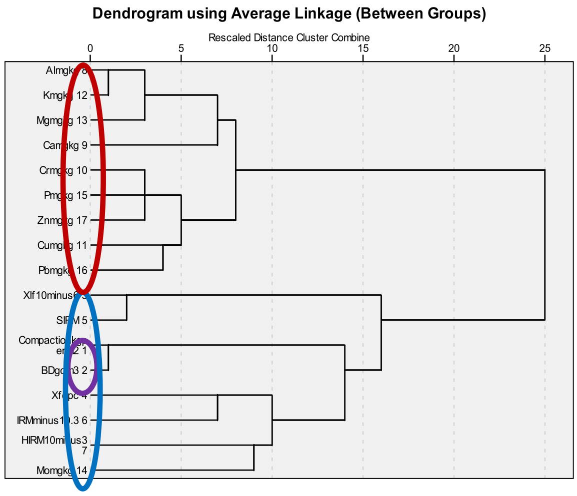

Figure 43 Dendrogram of Bay 1 Clusters

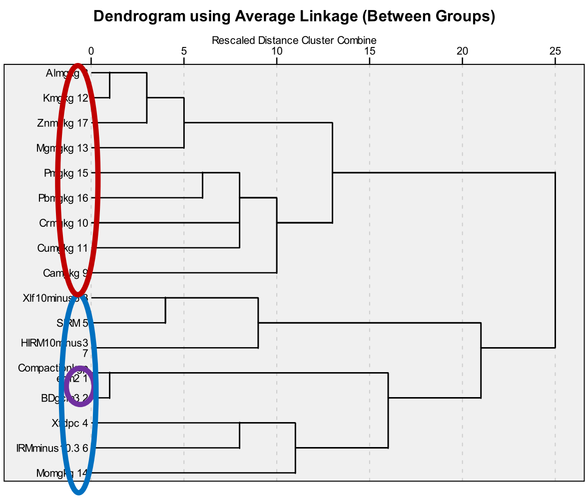

Figure 44 Dendrogram of Bay 2 Clusters

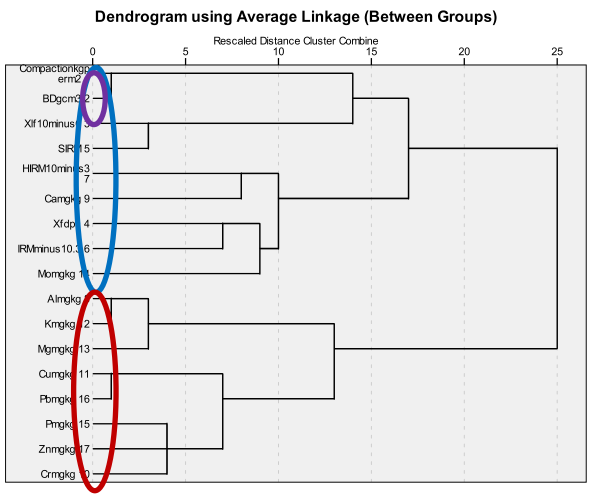

Figure 45 Dendrogram of Bay 3 Clusters

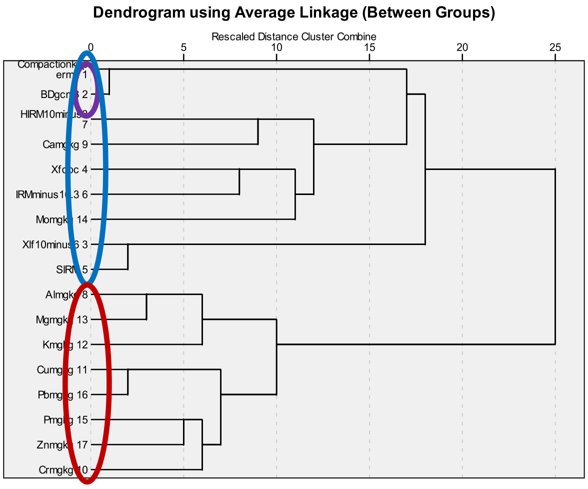

Figure 46 Dendrogram of Bay 4 Clusters

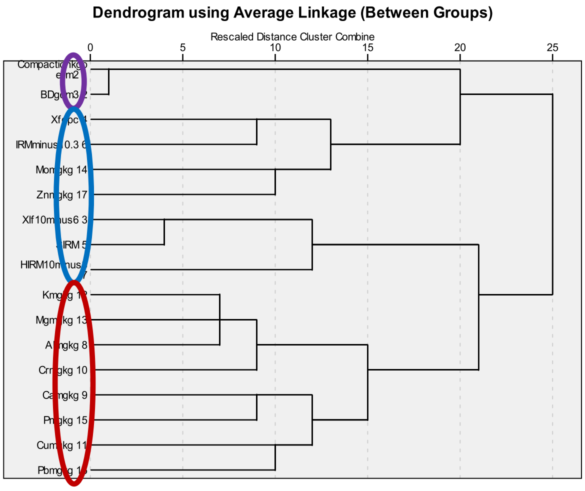

Figure 47 Dendrogram of Bay 5 Cluster

and Mg belong to ferro-magnesian minerals that form from rock-forming minerals, Ca may be associated with the mineral magnetism cluster due to its relation with iron oxides in soil following weathering and thus detected through these compositions.

In Section 5.4, mineral magnetism analysed the relationship between susceptibility (χ) and element variables, plus χ and Saturated Isothermal Remanent Magnetism (SIRM), to determine if these techniques could form an alternative method of detecting pollutants in soil samples. Resulting data would confirm whether it was possible to determine a relationship between geochemical/heavy metal variables and mineral magnetic measurements.

5.3 Data Distribution and Visualisation using One-way ANOVA and Boxplots

Further support of the relationships between the variables and the comparison of their effects on the different parking bays were shown through boxplots and One-Way ANOVAs.

Use of boxplots provided quick comparison of data sets, making pollution dispersion between the parking bays more straightforward to distinguish. One-Way ANOVA evaluates the mean value(s) of one for more groups based on a factor or variable, with the assumption that the factor/variable is distributed normally (Archambault 2000). Using One-Way ANOVA will determine if variable distribution is uniform across the parking surface. The following tables and figures present variation of surface compaction readings taken from across the vegetative parking area and of elemental concentrations extracted from randomly-selected soil samples, highlighting the similarities and differences of the VPS.

5.3.1 One-Way ANOVA Assessing Compaction and Element Concentrations Across the VPS

Subjecting compaction and element concentration data to One-Way ANOVA determined if distribution of the variables was significantly different across the VPS. Summarising significance values (P= 0.05) in Table 27, it was established that all variables, with the exception of Mo (0.476), displayed significant differences in means for pressure (compaction) and concentrations (elements) across the VPS. This revealed that the parking of vehicles had a significant effect on the VPS from the variables analysed. Mo concentrations sampled from across the VPS did not show much variation, thus resulting in the acceptance of a null hypothesis, that there was no significant difference between the control area and the parking bays.

Table 27 One-Way ANOVA for Compaction and Elements from the VPS (P = 0.05)

	One-Way ANOVA for Compaction and Elements from the VPS (P = 0.05)										
	Compaction	**Al**	**Ca**	**Cr**	**Cu**	**K**	**Mg**	**Mo**	**P**	**Pb**	**Zn**
Sig.	0.000	0.000	0.000	0.000	0.003	0.000	0.000	**0.476**	0.008	0.000	0.015

As a simple One-Way ANOVA only established a difference in the means, the data was also subjected to Tukey Multiple Post-Hoc Comparison to determine the differences between the control area and the parking bays to test all possible 2-way comparisons, following a significant F test. Displaying homogenous subsets of mean data for each of the variables (see Appendix IIA for tables and standard error values), it was possible to determine the major differences between the means.

Referring to the Post-Hoc table for compaction (Table 28) the mean for the control area of the VPS is considerably lower than the parking bays, and the mean for Bay 1 is substantially lower than Bays 2-5. Mean data for Bays 2-5 did not significantly differ from each other. This data coincides with questionnaire responses, which indicated that car park users were more likely to park on Bays 2-5 as they were easier to drive onto (see Section 5.5).

Table 28 Tukey Multiple Post-Hoc Comparison for Compaction across the VPS

Compaction

Bay	N	Subset for alpha = 0.05		
		1	2	3
Control	27	3.01		
1	84		3.80	
3	86			4.30
2	81			4.33
5	85			4.45
4	83			4.49
Sig.		1	1	0.39

Table 29 summarises the homogenous subsets for each of the elements (for full data, see Appendix IIB) and shows that Mo, P and Zn had no significant differences between sample means, as the data were contained in one subset. Tukey Post-Hoc comparisons identified that the remainder of the elements had some significant differences between the sample means (highlighted in grey); these significant means are identified in Table 29 through data that does not appear in more than one subset, i.e. Cu means show that data for Bay 3 and Bay 5 are not represented on both subsets thus these data are significantly different. Bays grouped in the same subsets showed no significant difference between each other.

Table 29 Summary table of Homogenous Subsets Arising from Tukey Multiple Post-Hoc Comparison

Subset	Al	Ca	Cr	Cu	K	Mg	Mo	P	Pb	Zn
1	**3, 4, Control, 5**	**3, 4, 1, 2, Control**	**2, Control, 3**	**3, Control, 2, 4, 1**	**4, 5, 3, Control**	**3, Control, 4,**	**All bays and Control**	**All bays and Control**	**3, Control, 4, 2**	**All bays and Control**
2	**Control, 5, 2, 1**	**Control, 5**	**Control, 3, 1**	**Control, 2, 4, 1, 5**	**Control, 1, 2**	**4, 5**			**4, 2, 1, 5**	
3			**3, 1, 4**			**5, 2, 1**				
4			**4, 5**							

Means for groups in homogeneous subsets are displayed.

a. Uses Harmonic Mean Sample Size = 62.029.

b. The group sizes are unequal.

The harmonic mean of the group sizes is used.

Type I error levels are not guaranteed.

5.3.2 Analysis of the VPS using Boxplots

Variation in the compaction readings obtained from each SCS Integra cell are shown as boxplots in Figure 48. Three distinct patterns emerged, grouping the boxplots into three similar pairs. The first boxplot represents the non-parked, control area of the VPS (labelled 0 on the chart). The data are not symmetric with the median value laying to the left-hand side of the boxplot. This reveals a greater number of increased compacted data values, making the distribution positively skewed.

Compared to the other bays, Bay 1 has the greatest variation in data. This bay is located next to the non-parked, outer area. The boxplot suggests that with greater variation, despite some data with the maximum readings possible by the penetrometer, other locations across the bay were not as compacted. This was confirmed by the long whisker representing readings between the minimum value and the first quartile.

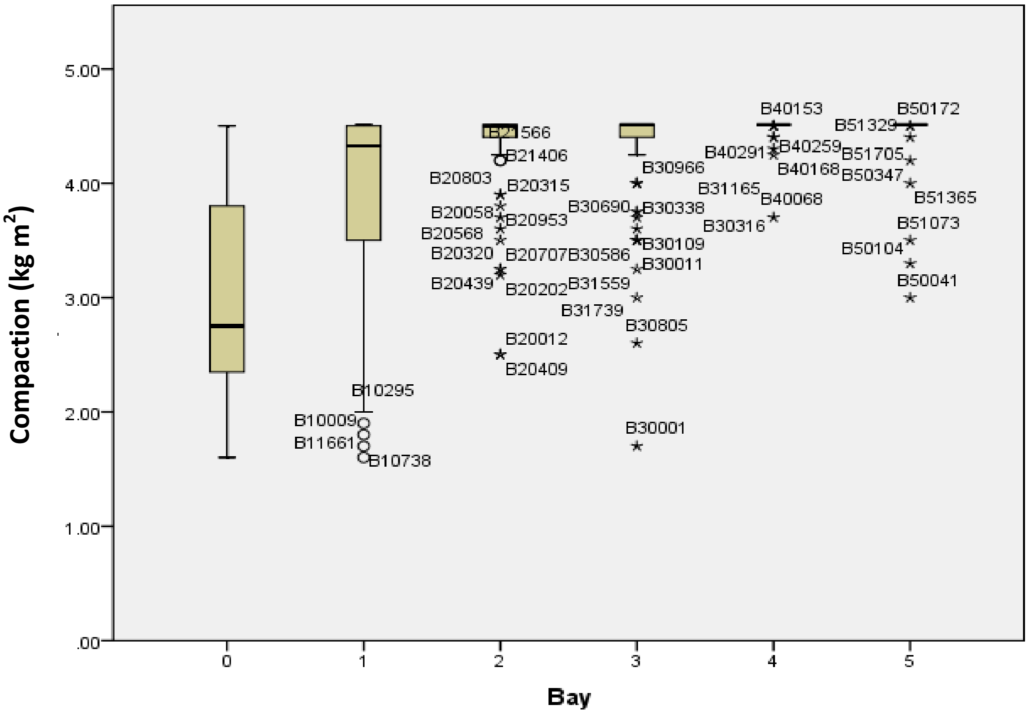

Figure 48 Boxplot displaying compaction (kg m²) across the VPS

The median value for the boxplot lay to the right-hand side of the IQR, determining that the main distribution of the data is negatively skewed. In addition to the whisker and right-skew median, four outliers showed evidence of locations in the VPS of Bay 1 where little compaction occurred; two areas at the top of the bay (far from the driveway), one in the centre of the bay and one close to the driveway. Reasons for this will be discussed in Chapter 6.

In the centre of the chart, Bays 2 and 3 show little variation in the data with the median values located at the top of the third quartile. The location of the median values and the whiskers on the left-hand side indicate that the data is negatively-skewed, which corresponds with the extreme outliers that represent the less-compressed values. Finally, Bays 4 and 5 show no variation in the data, with the exception of extreme outliers highlighed as asterisks. These data determine that the surface of these two bays was compacted with few locations across the area that penetreble with the penetrometer. From the boxplots, it can be determined that there is greater compaction the further away the bays are from the control area. This statement corresponds with data obtained from a questionnaire on parking habits (see Section 5.5), completed by regular users of the VPS, and is also shown in a map of the parking bays produced using ArcGIS (see Section 5.6, Figure 54).

Table 30 summarises boxplot data for each element, providing the minimum, median and maximum figures, which enabled the determination of the skewness of the data. In comparison to control, non-parked data, the majority of elements displayed positively skewed data, indicating that element concentrations increased across the parking surface. However, some bays revealed negatively skewed data in comparison to the control area, indicating that mean element concentrations were greater in the control samples; these are highlighted in Table 30. Cu, in particular, displayed negatively skewed data across Bays 1-4, showing that mean concentrations for Cu in these bays were less than the mean concentrations determined in the control, non-parked area. The skewed data in Table 30 indicated that skew was slight, thus the data remained untouched to preserve its distribution. Altering the distributions with reference to skewed data may have led to indirect effects on the variables thus leading to less reliable data.

Extensive research has taken place on pollutants in roadside vegetation. Several of these studies include Nouri and Naghipour (2002), Ramakrishnaiah and Somashekar (2002), Jankaitė, Baltrėnas and Kazlausklenė (2008) and Addo *et al*. (2012), who have all demonstrated elevated element concentrations in roadside soils, which had been influenced by traffic density and vehicle emissions.

Table 30 Summary Table of Boxplot Descriptive Statistics of Element Concentrations (highlighted cells indicate negatively skewed data)

		Al mg/kg	Ca mg/kg	Cr mg/kg	Cu mg/kg	K mg/kg	Mg mg/kg	Mo mg/kg	P mg/kg	Pb mg/kg	Zn mg/kg
OA	**MAX**	5247.86	4179.19	18.54	80.88	578.18	1155.68	0.59	604.10	54.63	104.70
	MIN	2210.81	1663.36	8.97	19.45	226.17	521.04	0.00	361.74	25.53	54.45
	MEAN	3816.36	2372.42	14.67	35.93	398.31	910.44	0.02	500.47	42.35	84.85
	MEDIAN	3768.28	2231.13	14.79	34.02	380.66	918.59	0.00	506.95	42.61	85.85
	SKEW	0.12	1.76	-0.56	3.30	0.35	-0.65	5.20	-0.38	-0.55	-0.57
Bay 1	**MAX**	6956.05	4020.58	23.95	60.12	844.37	1648.95	0.59	658.02	64.07	142.33
	MIN	2472.57	1394.58	10.97	25.55	207.47	635.44	0.00	371.93	33.51	54.36
	MEAN	4207.01	2199.63	16.05	37.34	435.52	1033.11	0.02	516.54	45.61	91.99
	MEDIAN	4024.37	2129.17	15.73	36.76	385.83	1005.83	0.00	520.77	45.10	90.46
	SKEW	0.57	1.11	0.78	0.98	0.95	0.78	6.11	0.20	0.53	0.59
Bay 2	**MAX**	7861.46	4880.72	49.77	57.40	1166.94	1704.66	0.80	725.17	54.92	129.38
	MIN	2421.89	278.34	0.10	28.76	180.98	604.24	0.00	347.32	32.72	55.02
	MEAN	4164.53	2302.59	13.91	36.66	447.78	1035.79	0.01	509.80	43.68	88.38
	MEDIAN	4076.27	2102.69	15.80	36.65	421.84	1027.72	0.00	503.98	43.28	87.25
	SKEW	0.75	1.50	1.17	1.78	1.25	0.57	8.61	0.50	0.13	0.26
Bay 3	**MAX**	5470.45	5362.53	34.81	44.03	670.98	1364.99	0.20	771.36	52.22	115.26
	MIN	2439.46	192.27	11.21	27.77	197.70	615.82	0.00	358.65	32.79	61.23
	MEAN	3700.54	2030.61	15.72	34.47	361.56	908.31	0.00	496.71	41.46	82.29
	MEDIAN	3631.38	1894.92	14.87	33.84	343.18	908.32	0.00	491.02	41.32	82.01
	SKEW	0.59	2.60	3.03	0.51	0.92	0.58	6.21	0.92	0.31	0.46
Bay 4	**MAX**	4955.50	5148.16	22.40	47.88	563.44	1219.63	15.61	688.88	54.81	115.19
	MIN	2654.96	1306.92	13.34	27.48	49.76	636.62	0.00	409.83	32.50	61.48
	MEAN	3713.01	2157.01	16.92	36.86	342.43	936.52	0.20	531.78	43.15	83.75
	MEDIAN	3638.17	2046.00	16.70	36.99	349.05	926.28	0.00	523.12	43.21	81.96
	SKEW	0.38	3.04	0.42	0.03	-0.27	-0.02	9.10	0.68	-0.03	0.65
Bay 5	**MAX**	5828.57	6524.05	29.39	96.95	776.58	1466.76	0.20	1177.35	111.50	993.11
	MIN	567.84	237.57	13.80	15.93	93.09	760.69	0.00	424.79	35.43	15.93
	MEAN	3856.60	2697.92	18.35	38.66	355.58	1004.13	0.01	527.15	46.19	106.51
	MEDIAN	3825.93	2475.50	17.91	37.51	342.92	974.67	0.00	513.88	44.98	90.08
	SKEW	-0.70	1.70	1.31	3.97	1.17	0.75	5.65	4.46	4.91	7.55

5.4 Magnetism

Past research into elemental concentrations in topsoil has identified elements with good correlation with low frequency susceptibility (χlf), particularly Cu, Pb and Zn (Chan *et al*. 1997), with Kim *et al*. (2010) stating that heavy metals from vehicle emissions (including Cd, Cr, Fe, Mn, Ni, Pb and Zn) highlighting strong relationships with χlf. Evidence such as this indicated that mineral magnetism may provide a useful means of determining vehicular pollutants across a VPS, utilizing it as a proxy to geochemical analysis.

5.4.1 Relationship between Susceptibility and Elements Concentrations

For each of the sampling areas, the elemental concentrations were plotted against χlf, each showing the correlations between the two variables and determining if any of the elements indicated pollution. In order to determine the effect of pollution that may originate from or be enhanced by vehicles parking on the VPS, it was necessary to establish the natural element concentrations of the soil by analysing an area that was not parked on. The following table identifies correlations coefficients between element concentrations and χlf, obtained from the VPS.

Table 31 Correlation Coefficients (R^2) Summary Table Between χlf and Geochemistry

Location	Al	Ca	Cr	Cu	K	Mg	Mo	P	Pb	Zn
Control	0.013	**4.73E-04**	0.008	0.02	0.009	**1.17E-05**	0.003	**0.061**	0.017	0.002
B1	0.008	0.02	0.032	**0.087**	0.01	0.012	**4.03E-04**	**0.055**	0.036	0.005
B2	0.006	0.029	0.021	0.039	0.01	0.017	**1.37E-05**	**1.07E-05**	**0.072**	0.002
B3	**1.84E-05**	0.01	0.002	0.008	0.001	0.002	0.017	0.001	0.018	0.006
B4	0.003	**1.27E-04**	0.087	**6.24E-06**	0.005	0.001	0.01	**1.44E-04**	**3.98E-04**	0.001
B5	0.007	0.001	**2.15E-04**	**9.41E-04**	0.003	0.005	0.004	**2.81E-04**	0.032	**1.79E-04**

R^2 values in Table 31 show that there is little correlation between the elements and χlf. Largest R^2 values are displayed in grey; however, despite these figures indicating more positive correlation in comparison to the remainder of the table, the figures still show little significant correlation with χlf. A number of elements showed no linear correlation with χlf; these values are highlighted in dark blue in Table 31.

Little correlation may have been detected in samples obtained from the VPS, however, previous studies have identified good correlation with heavy metals which makes the use of mineral magnetism a possible alternative method for contaminant detection, even though quantification of total pollutant loadings would pose a difficult problem (Beckwith *et al*. 1986). Blundell *et al*. (2009), Morton-Bermea (2009), Canbay (2010), Kim *et al*. (2010) and Zhang *et al.* (2011) demonstrated positive correlation between metal concentrations and χ, suggesting that χ could provide a reasonable indication of heavy metal contamination, as an alternative method of pollution detection. However, similar to this research, investigations by Canbay (2010) determined poor relationships between heavy metals and χ, despite detecting high concentrations of particular heavy metals in soil samples.

5.4.2 The relationship between Saturated Isothermal Remanent Magnetism (SIRM) and Low Frequency Susceptibility (χlf)

An additional approach which may provide a proxy indicator of heavy metal pollution in soil is determining the relationship between Saturated Isothermal Remanent Magnetism (SIRM) and Low Frequency Susceptibility (χlf), which have shown to have a strong linear correlation (Lu, Wang and Guo 2010). Studies combining chemical composition analyses and mineral magnetics by Lu *et al*. (2006; 2007), Yang *et al*. (2007), Blaha *et al*. (2008) and Lu, Wang and Guo (2010) have suggested good associations with magnetic parameters and heavy metals. Using Microsoft Excel 2007, ratios between SIRM and χlf were determined using the SLOPE function, where known means of the independent and dependent variables returned a slope of linear regression through the data points plotted in Figure 47. The equation for the slope of the regression line used in the SLOPE function (Equation 2) determined the ratios shown in Table 32.

Equation 2 Slope of the Regression Line in the Microsoft Excel 2007 SLOPE Function

$$b = \frac{\sum (x-\bar{x})(y-\bar{y})}{\sum (x-\bar{x})^2}$$

Table 32 Ratios derived from SIRM and χlf Relationships across the VPS

Area	Control	Bay 1	Bay 2	Bay 3	Bay 4	Bay 5
Ratio	18.07	20.56	18.12	16.29	21.51	16.8
R^2	0.72	0.79	0.62	0.66	0.86	0.70

From Table 32, the background readings from non-parked area produced a slope of 18.07. Bays 1 to 5 had slopes with values from 16.29 to 21.51. Comparing these values to Figure 48 (Charlesworth 1994), samples obtained from Bays 3 (16.29) and 5 (16.80) provided readings that were close to the value taken from Polluted Woodland Organic Matter. Bays 1 (20.56) and 4 (21.51) had slope values that reflected greater similarity to SD Magnetite. Bay 2 (18.12) had a similar slope value to that obtained from the non-parked background readings. R^2 values resulting from linear regression determined that the relationship between SIRM and χlf showed significant correlation across the VPS, particularly Bay 4 (R^2 = 0.86).

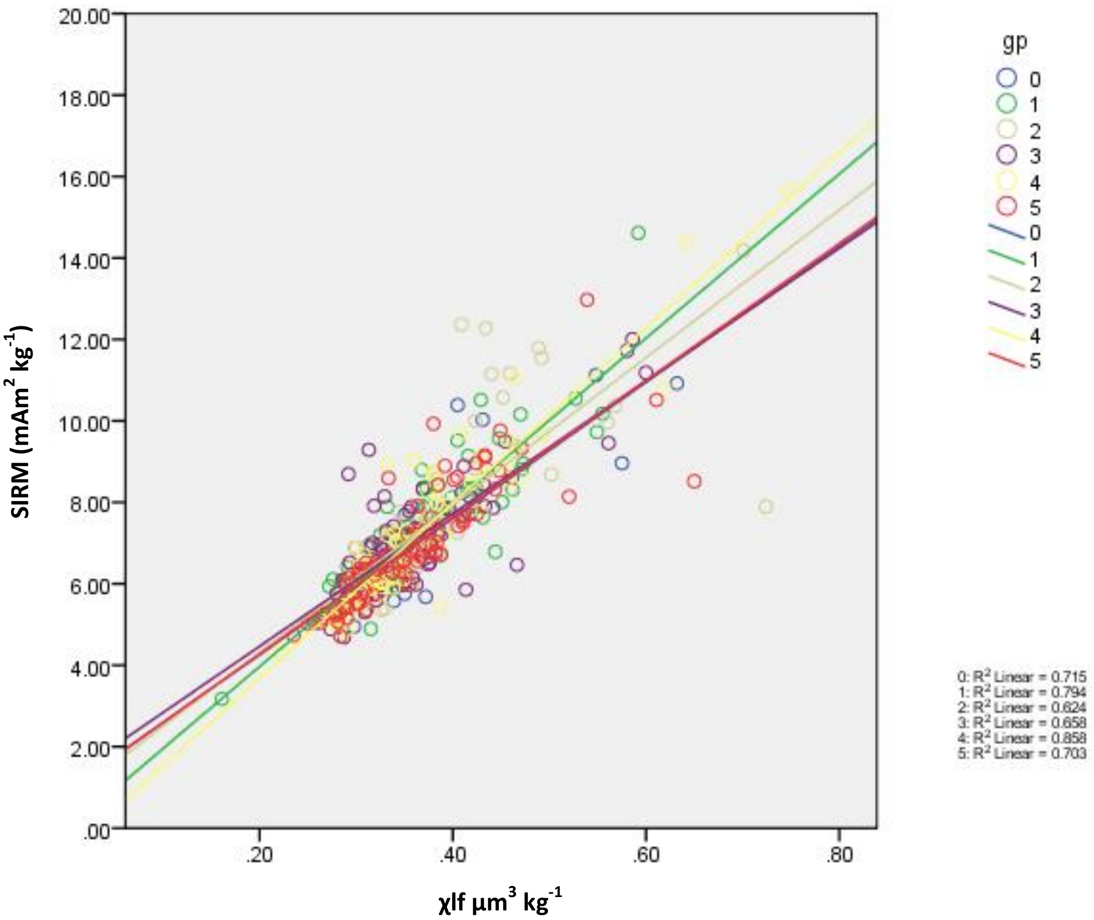

Figure 49 The relationship between saturated isothermal remanent magnetism (SIRM) and low frequency susceptibility (χlf) in VPS samples.

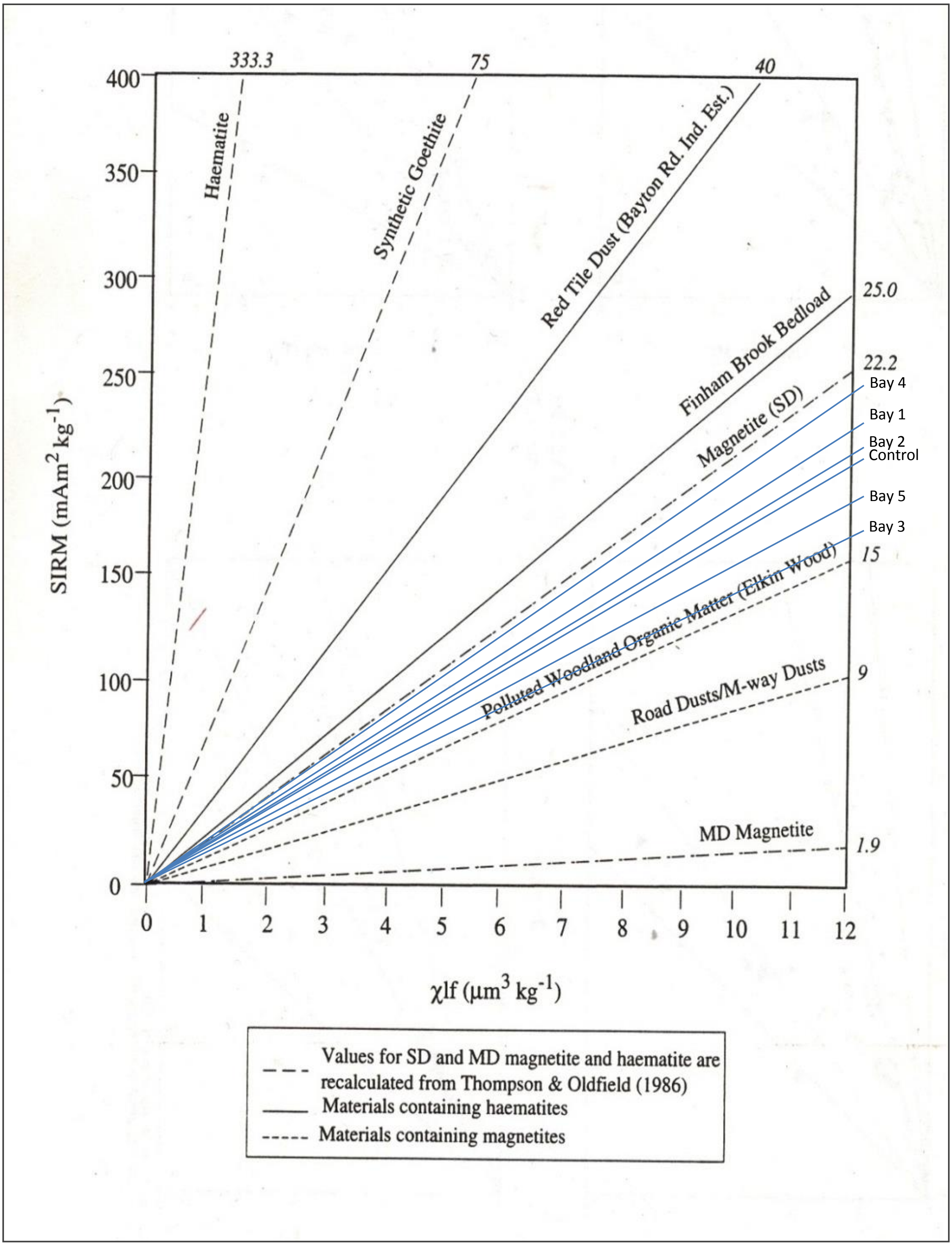

Figure 50 SIRM/ χ lf Ratios for sets of Polluted Materials (Charlesworth 1994). VPS Sample SIRM/ χ lf ratios from Table 31 for VPS included.

With reference to Figure 50, slope values recorded in Table 32 identified that the samples taken from all car park bays, including the non-parked area, have materials containing magnetite. It was also noted that despite the SIRM/χlf ratios indicating that VPS samples contained magnetite, when plotted on Figure 49, data points displayed low concentrations of the pollutants and thus lay close to the origin of the chart.

5.5 Questionnaire of parking habits

Enhancing the VPS data by investigating the usage of the parking bays by the staff from Clinton Primary School, determined whether the frequency of parking on particular bays had an effect on the resulting data. A questionnaire (see Appendix IID) designed to investigate the opinions of the staff that parked on the school site, discovered their regular parking choices, established if they had particular reasons for parking in certain locations, questioned their attitudes to the VPS bays and determined if they would change their parking habits.

The 10 questionnaires revealed that 40% of the respondents parked on the 'hard' surface, with each of these claiming that this was a continual habit they had and that the bays were available when they arrived at the site. From the remaining respondents, only 10% stated that they solely parked on the VPS (at least four times a week) and the other 50% parked on both surfaces, using the VPS when there were no 'hard' surface parking bays left. Sixty percent of the respondents stated that from the VPS bays available, Bay 2 (20%), Bay 3 (10%), Bay 4 (10%) and Bay 5 (20%) were favoured, with the majority of the drivers parking forwards into the bays. The most common reason for the choice of VPS bay was that the location that was chosen was usually available when the driver arrived. One respondent stated that they chose a particular bay for its proximity to the school building, another for the ease of driving into the bay and another for making it easier for others to park around them.

When asked which VPS bays would be used if the 'hard' surfaced parking bays were unavailable, Bay 3 came out as the most preferred, along with Bay 5. Bays 2 and 4 were also chosen but were not as favourable. From all of the responses of those who did not favour the VPS bays only, consideration of using these alternative bays would be made in the future. If the VPS parking spaces remained empty, 10% of the respondents expressed that they would walk across the VPS bays as a short cut, 10% stated that they would occasionally use them as a short cut and the remainder would use official pathways only.

When referring to parking in wet weather, 40% of the respondents stated that this would affect their decision to park on the VPS parking spaces. The majority of these respondents thought that there may be a possibility of their footwear sinking into the surface and the remainder thought that vehicle manoeuvrability on the surface may be difficult.

The final question asked about their opinions of the vegetative spaces. Approximately 50% thought that the VPS bays were more aesthetic than the 'hard' surfaced bays, 80% agreed that the VPS provided extra parking space, 20% believed that the VPS provided extra drainage for rainfall and 10% assumed that the vegetative parking spaces had no effect on the clean-up of contaminants. Fifty percent of the respondents did not know whether the VPS bays had any influence on the drainage of rainfall, and the majority did not know whether these bays would help control contamination of the environment. Final observations found that the respondents agreed that the vegetative spaces provided additional space to park and that they didn't seem to require much extra maintenance than the 'hard' surfaces.

5.6 Using Geographical Information Systems (GIS) for the visual representation of compaction, geochemical and magnetism data from a VPS

GIS was used to create an interactive map to display relationships between spatial data from a small-scale field trial. Analyses and data displayed in tables and charts provided information about the distribution of pollutants across the surface and how significant relationships were in comparison with compaction and mineral magnetism. However, data in these formats can sometimes be difficult to assess. Creation of an interactive map allowing the possibility of turning spatial data layers on and off to provide visual, informative trends would satisfy the aim of making this research a novel concept, following previous studies focusing at larger scales.

Identifying Clinton Primary School using OS MasterMap® and Digimap® (http://edina.ac.uk/mastermap/), a .gzip file was acquired from the website and uploaded to ArcGIS®, providing a topographical layer to base the map on (Figure 51). This file included the local roads (grey) and main school building (brown) and the car park, including the area converted to VPS (green).

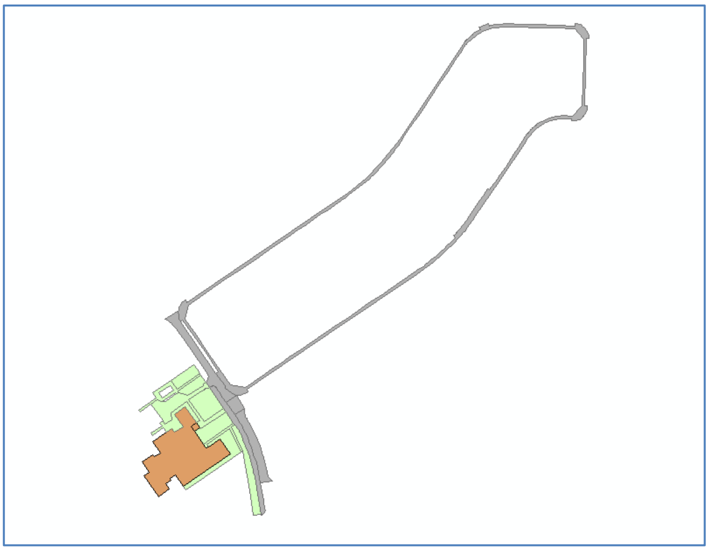

Figure 51 ArcGIS Screenshot of Clinton Primary and Local Road Network Topography Layer (1:2000)

Having recorded the GPS coordinates from the corners of each bay, it was possible to determine the location of the parking bays on the topographical layer and manually include the bays as polygons (Figure 52). With main features in place, compaction and geochemical data containing x, y coordinates were uploaded to the map to create layer files. Figure 53 displays individual points symbolising the random locations from which the samples were obtained. Compaction data was logged across the VPS, covering the whole surface.

Figure 52 Addition of Parking Bay Polygons (1:200)

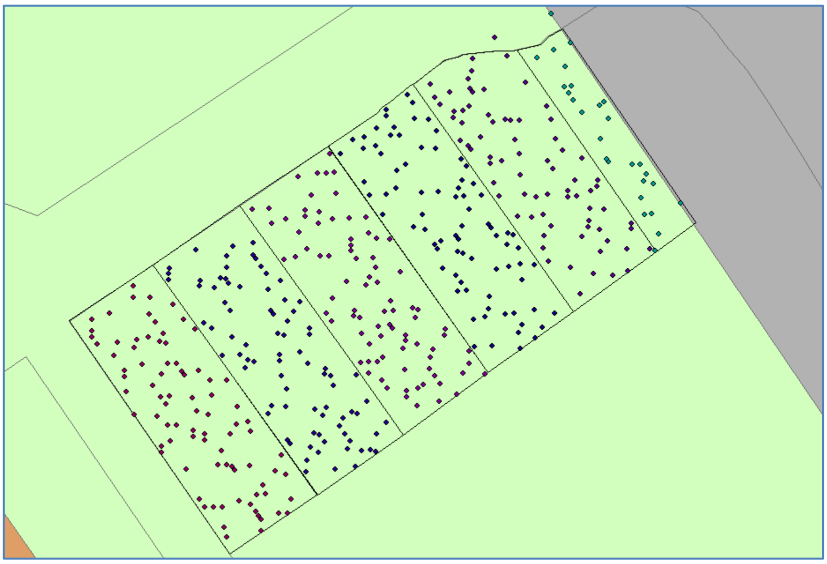

Figure 53 Individual data points locating element samples (1:85)

5.6.1 Compaction across the VPS

Data in point form proved difficult to determine trends and relationships between the variables thus individual points were converted to contour layers (Chapter 3, Section 3.10). Contour lines displaying compaction lay close together, making it difficult to distinguish trends, thus the layer was converted to TIN (Figure 54), showing a 3D layer representation of the data which connected compaction observations (Heywood, Cornelius and Carver 2006). Referring to the legend, darker shades indicated areas of low compaction, which are more abundant in the non-parked, control area, Bay 1 and Bay 2. A trend can be seen across the VPS; compaction increases the closer the bay is to the school building. This pattern partly corresponds with questionnaire responses; respondents favoured four of the five bays (Bay 2 (20%), Bay 3 (10%), Bay 4 (10%) and Bay 5 (20%)). These results do not, however, specify how often these bays were used by the respondents, despite their preferences of Bay 2 and Bay 5.

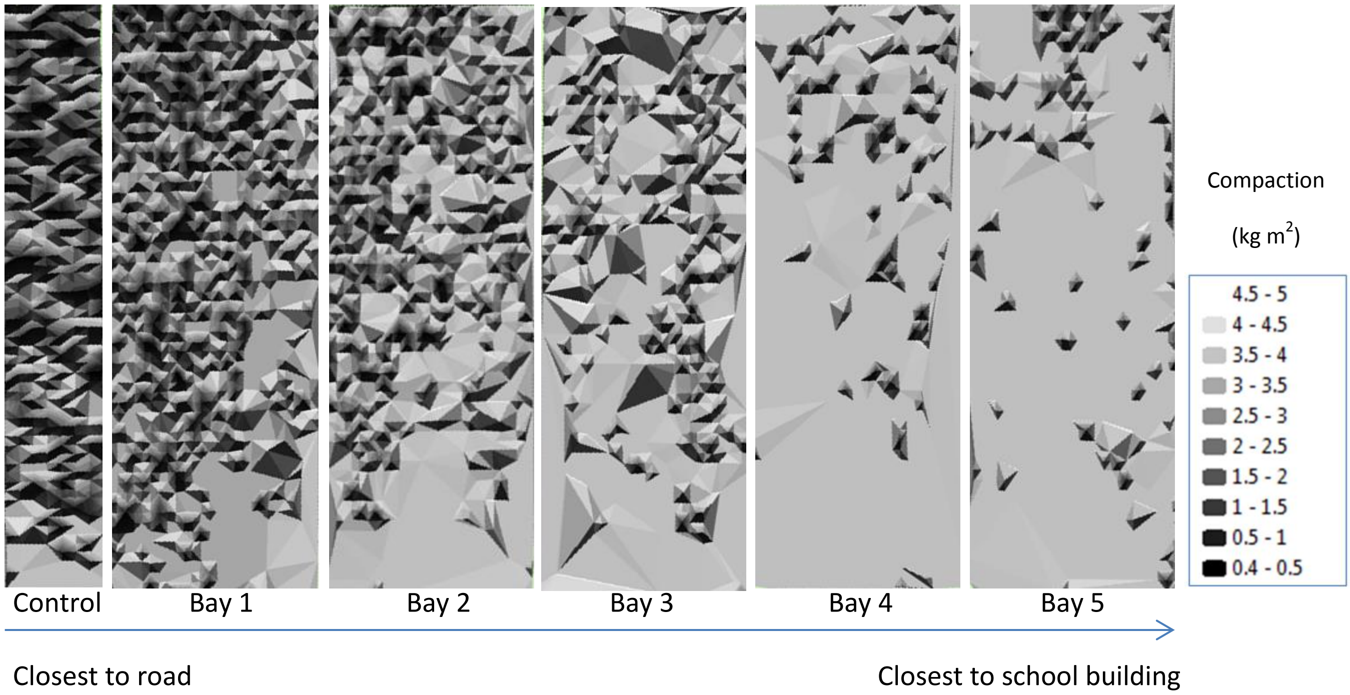

Figure 54 TIN layer of VPS compaction (not to scale)

GIS provided a suitable method for visualising soil compaction across the VPS, presenting a TIN map layer displaying data through graduated shading; darker shades indicated less compacted locations and those that were more compacted, were portrayed by the light grey, 'smooth' areas across the parking bays (Figure 54). The reinforced Integra blocks (included in the construction of the VPS) prevented deep surface compaction, restricting the effects to the top layer of soil.

5.6.2 Element concentrations across the VPS

Use of contour lines to represent changes in element concentrations across the VPS did not provide a suitable means for distinguishing change between data points, due to the small scale at which the map was plotted. Points were converted to TIN layers (creating the basis of a 3D layer), which after a further transformation to kriging, transformed the data into interpolating areas that provided an estimation of concentrations for non-sampled locations (i.e. weighted sums of the adjacent sampled concentrations (Rodríguez Martín, López Arias and Grau Corbí 2006)). Resulting layers made determination of data trends much easier to distinguish (Figures 55-64).

Samples from the non-parked control area indicated greater element concentrations in both the centre of the area and to the edge of the section adjacent to Bay 1 (see Chapter 3, Section 3.5, Figure 22 for diagram of the bays). The majority of the bays displayed greater element concentrations at the edge of the areas where vehicles drove onto the bays, with several exhibiting areas of high concentrations which seem to represent the location over which the engine may rest when a vehicle is parked. With the exception of Ca and Mo, Bay 4 exhibited higher concentrations across the sampling locations in comparison to the remainder of the VPS.

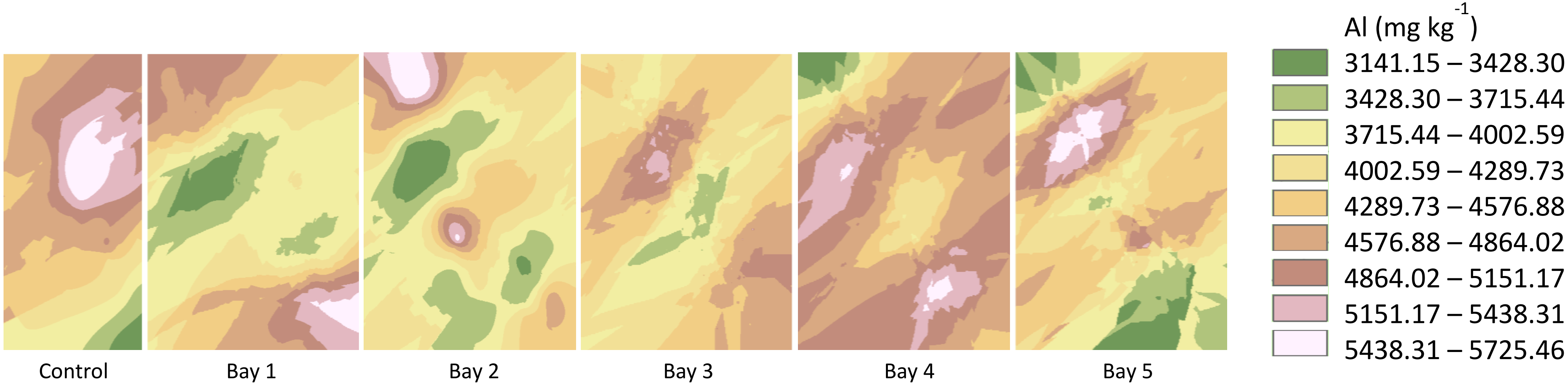

Figure 55 Al Kriging on VPS (not to scale)

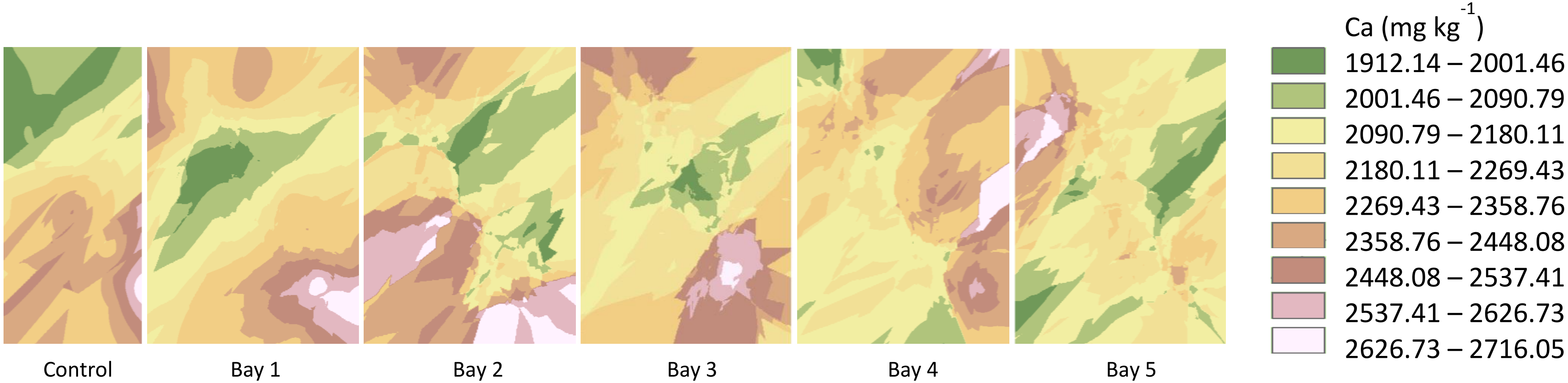

Figure 56 Ca Kriging on VPS (not to scale)

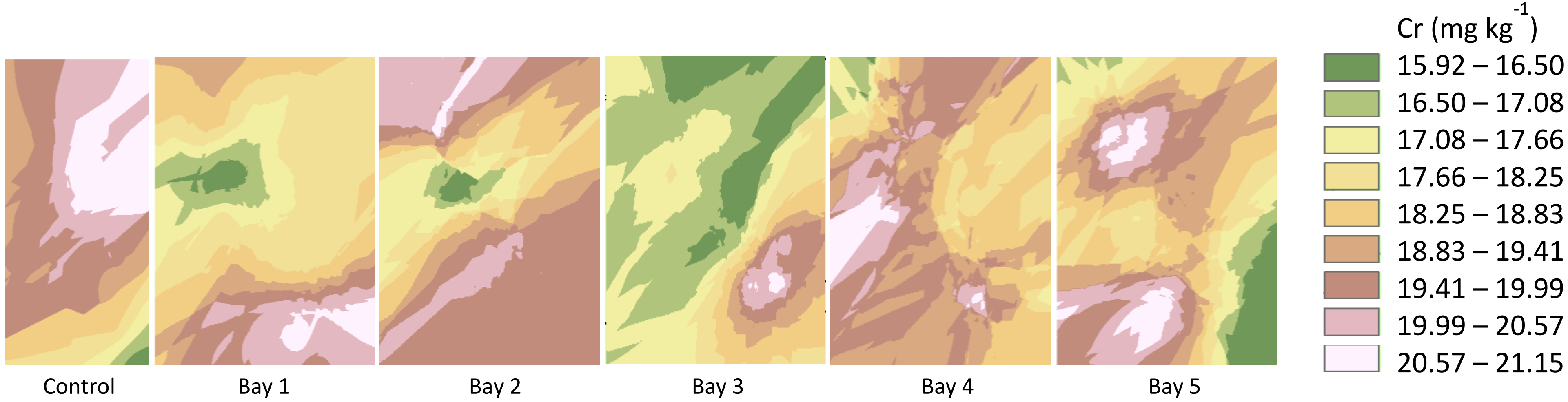

Figure 57 Cr Kriging on VPS (not to scale)

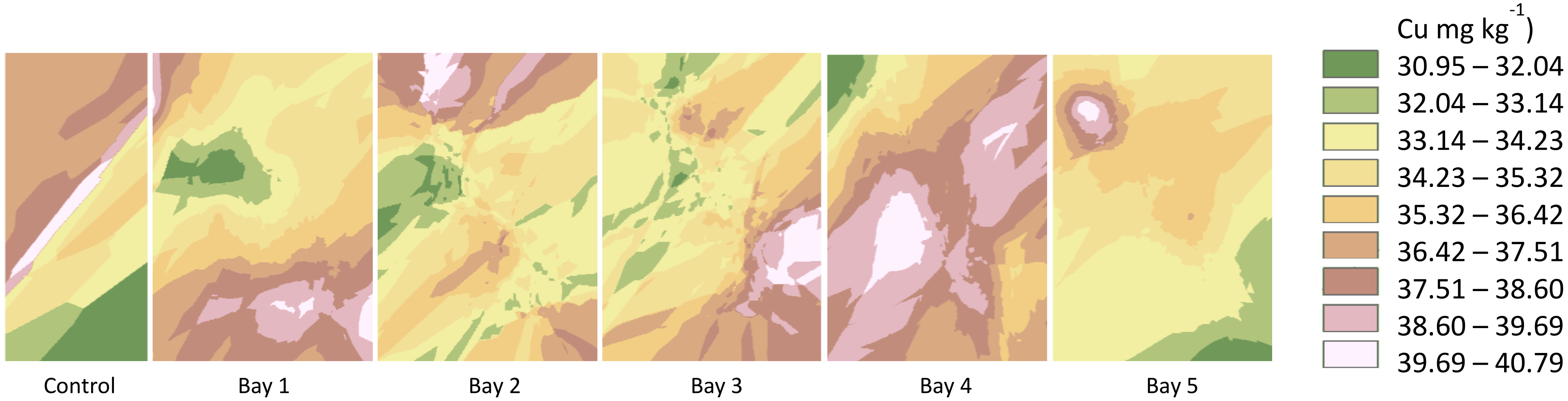

Figure 58 Cu Kriging on VPS (not to scale)

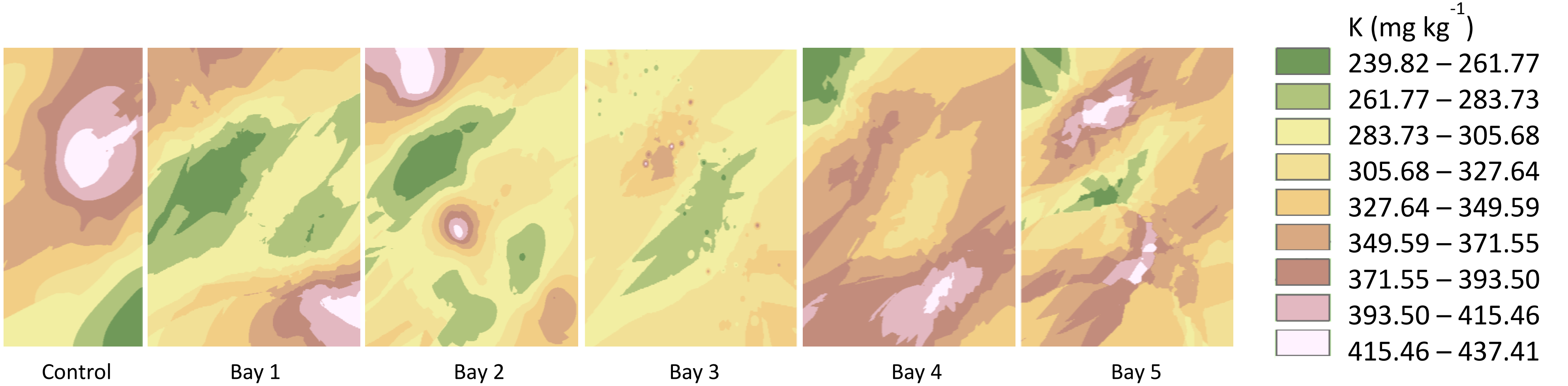

Figure 59 K Kriging on VPS (not to scale)

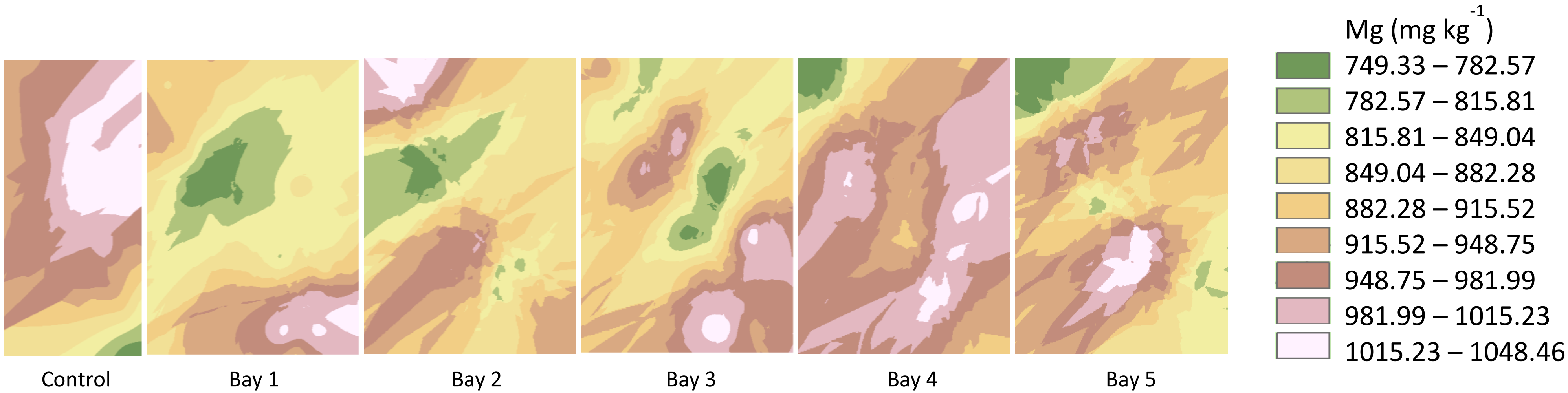

Figure 60 Mg Kriging on VPS (not to scale)

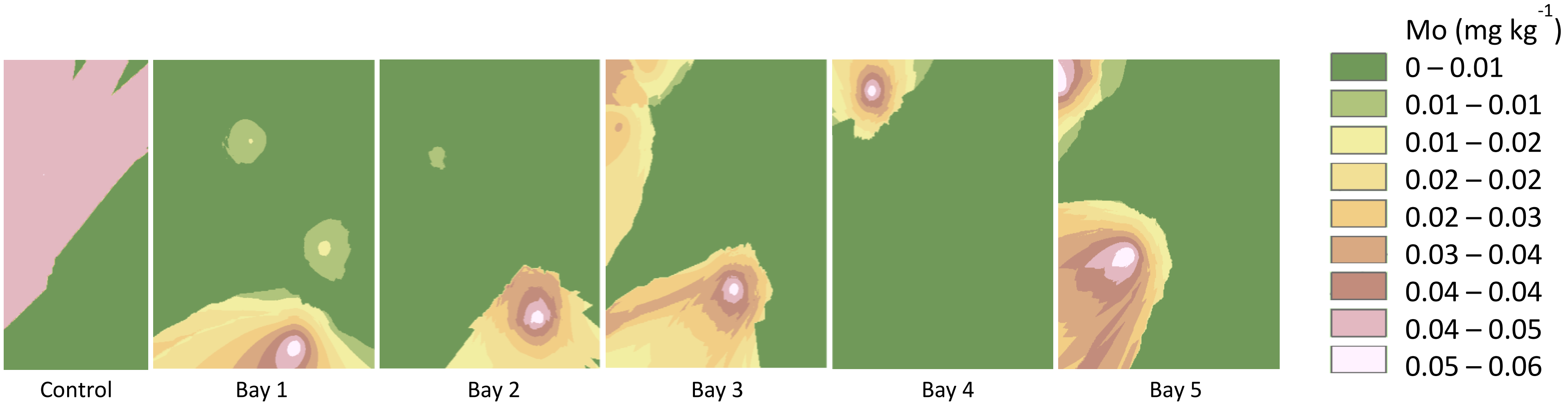

Figure 61 Mo Kriging on VPS (not to scale)

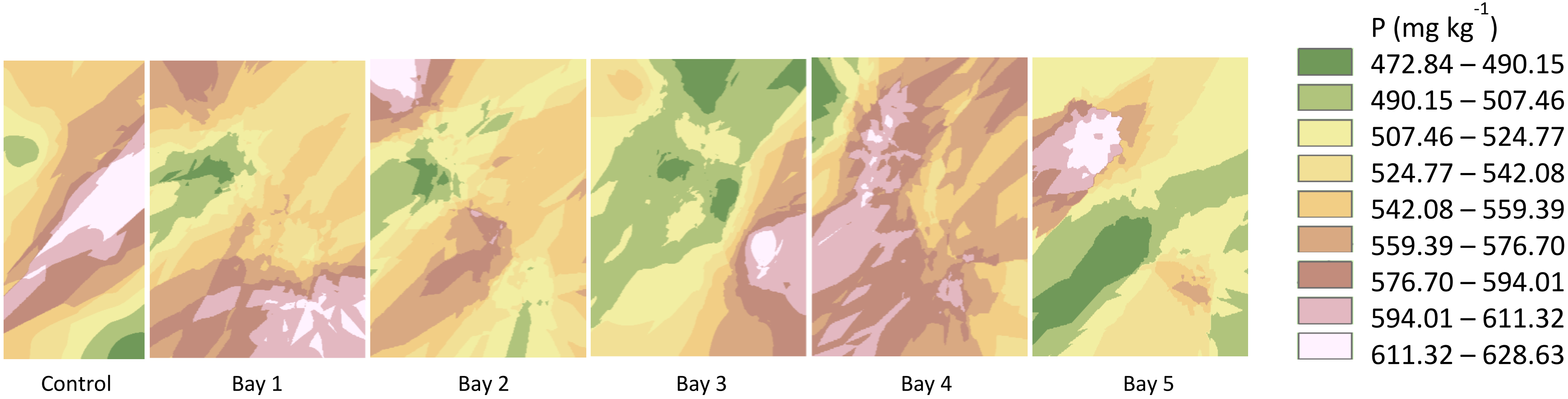

Figure 62 P Kriging on VPS (not to scale)

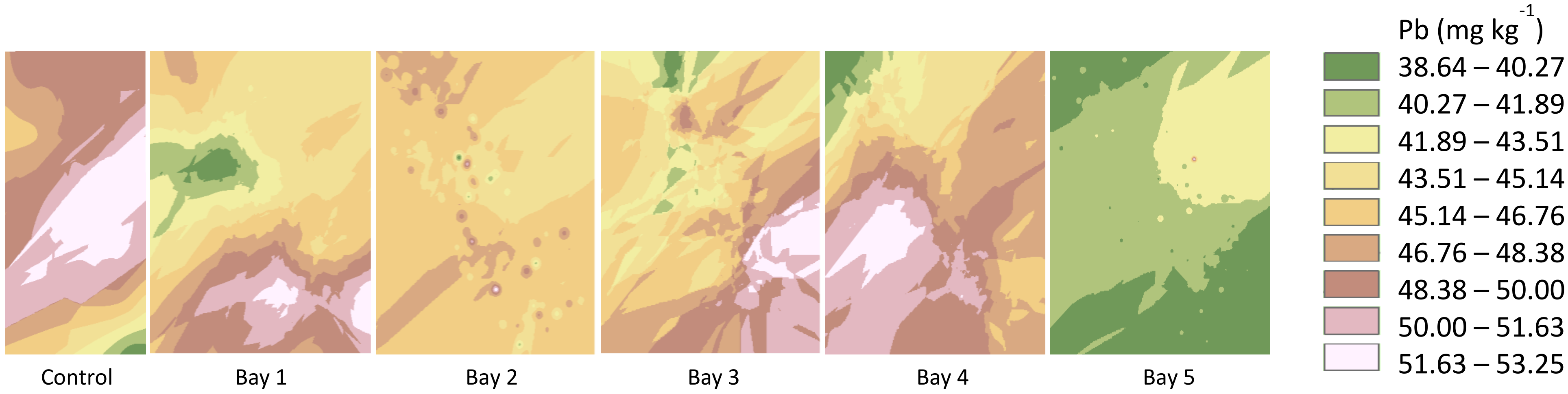

Figure 63 Pb Kriging on VPS (not to scale)

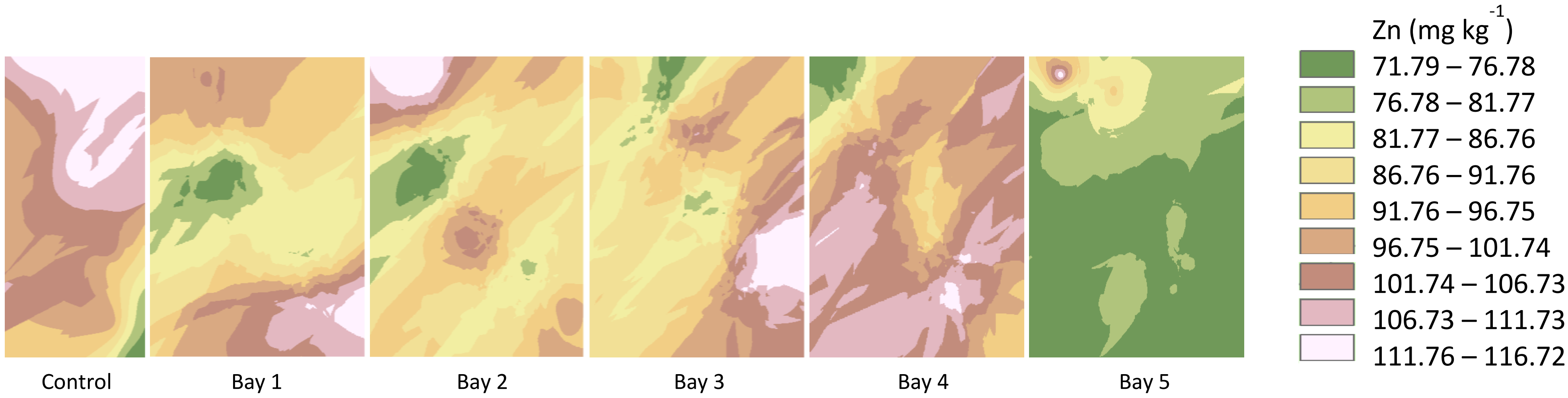

Figure 64 Zn Kriging on VPS (not to scale)

A series of profile charts were also generated from element concentration data, illustrating their dispersal across the VPS and supplementing the kriging arrangements (Figures 55-64). Addition of profile lines to parking bay polygons that crossed on both the width and the length axes of the sampling areas, determined element concentrations based on TIN measurements. These data were plotted as line charts (Figures 65-74 and Appendix IIE), emphasising concentration change across the bays. Table 33 provides a summary of the profiles created by element concentrations across the VPS.

As shown in the charts (Figures 65-74) and element profile trend (Table 33), higher element concentrations in the control sampling areas were mainly distributed in the centre of the sampling location. As this location was not subjected to parking, there was little parking influence on element distribution. Examining the charts showing element dispersal across each of the parking bays, it is possible to see that greater concentrations are mainly situated close to the edges of the bays, particularly where vehicles drove onto the surface and at the edges where their tyres rested when parked.

Table 33 General Element Concentration Trend

Location	Bay end nearest driveway	Centre of bay	Bay end nearest lawn
Control	K, Mo, Pb	Al, Ca, Cr, Cu, K, Mg, Mo, P, Pb, Zn	Zn
Bay 1	Al, Ca, Cr, Cu, K, Mg, Zn	Cu, Mg, Pb,	Al, Ca, Cr, K, Mo, P, Pb, Zn
Bay 2	Al, Cr, Cu, K, Mg, Pb, Zn	Al, Ca, Cu, K, Mg, P, Zn	Cr, Mo, Pb
Bay 3	Al, Ca, Cr, Cu, K, Mg, Zn	K, Pb	Al, Ca, Cr, Mg, Mo, P, Pb
Bay 4	Al, Ca, Cr, K, Mg, Mo, P, Zn	Cu, Mo, Pb	Al, Cr, K, Mg, P, Pb, Zn
Bay 5	Ca, Cr, Cu, K, Mg, P, Pb, Zn	Cu, Mg, Mo	Al, Ca, Cr, K, P, Pb

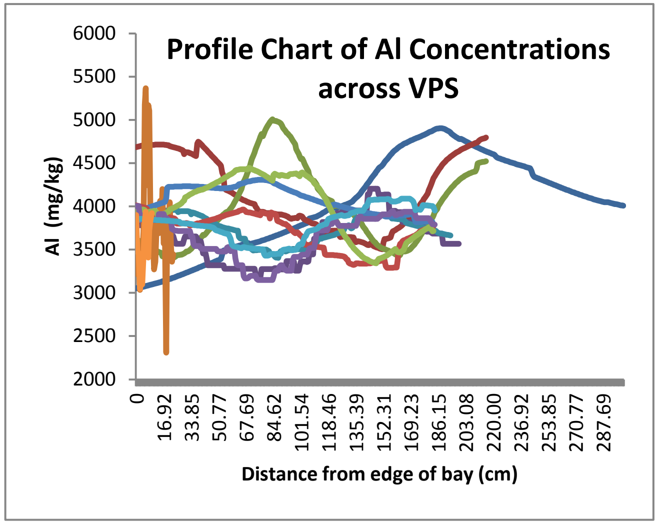

Figure 65 Al (mg/kg) across the VPS

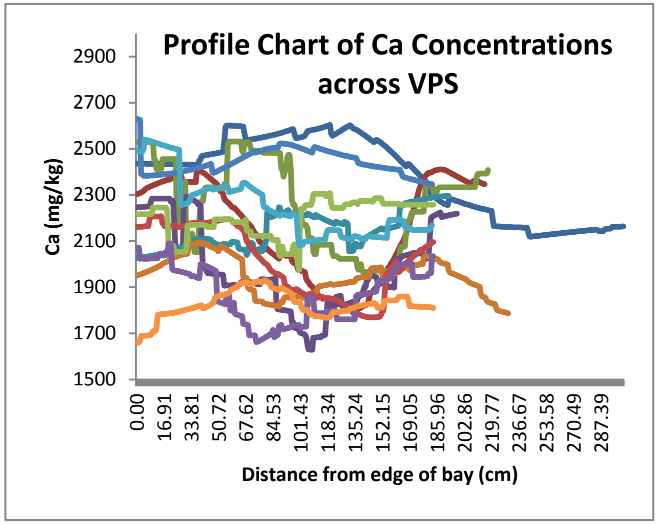

Figure 66 Ca (mg/kg) across the VPS

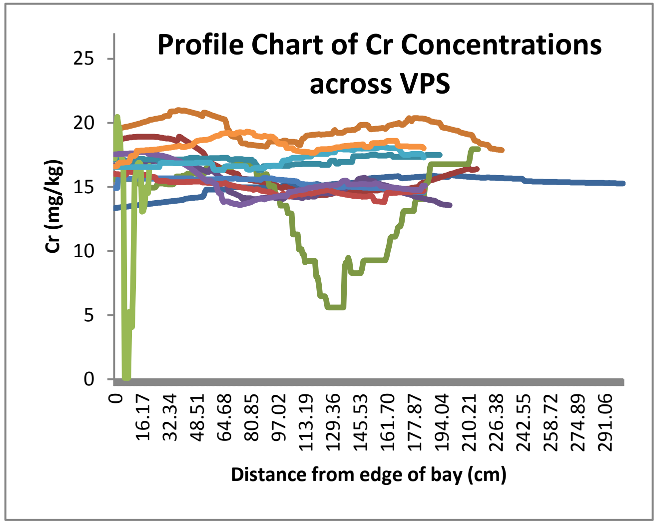

Figure 67 Cr (mg/kg) across the VPS

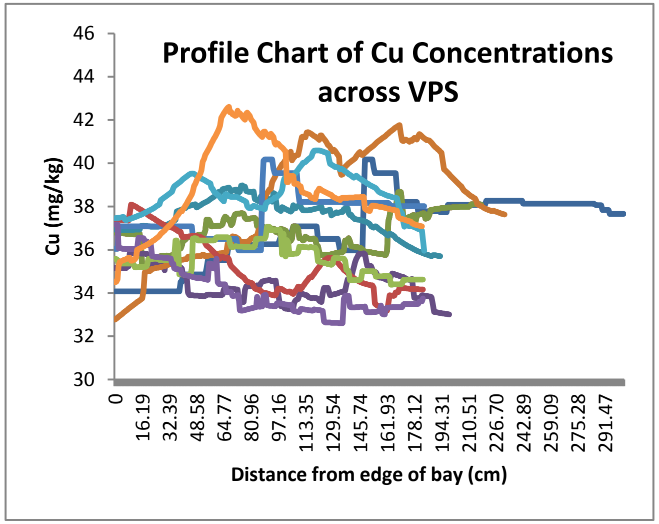

Figure 68 Cu (mg/kg) across the VPS

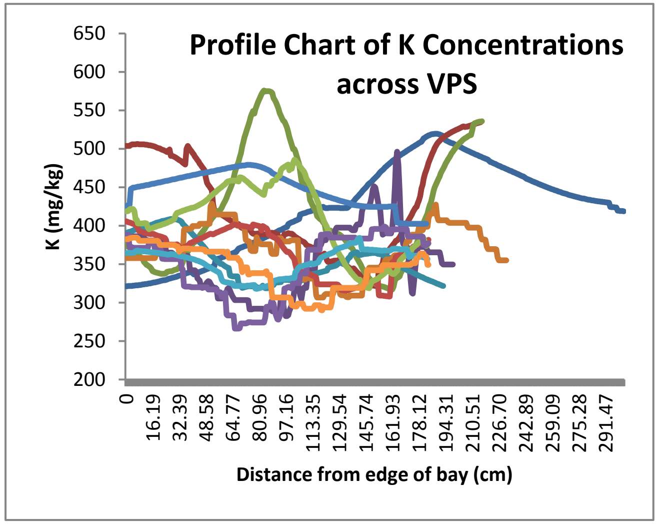

Figure 69 K (mg/kg) across the VPS

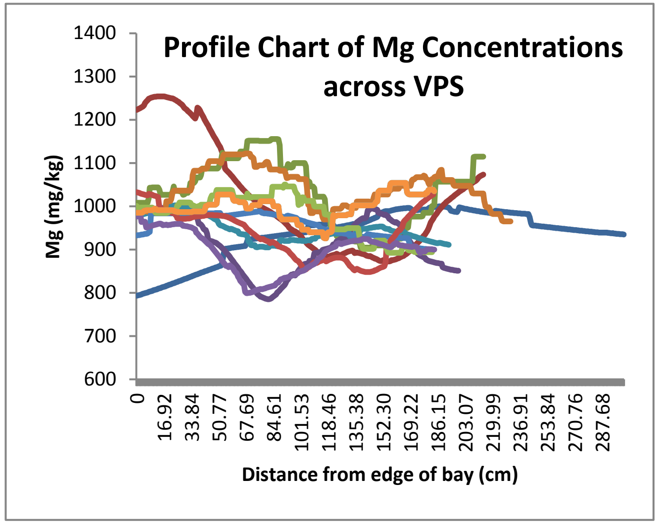

Figure 70 Mg (mg/kg) across the VPS

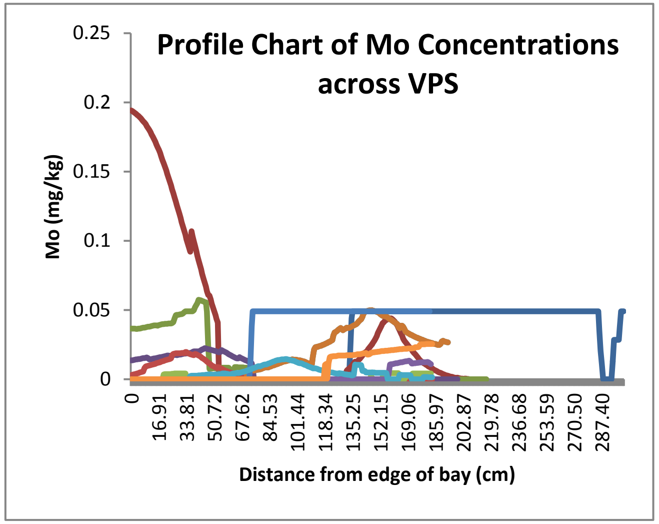

Figure 71 Mo (mg/kg) across the VPS

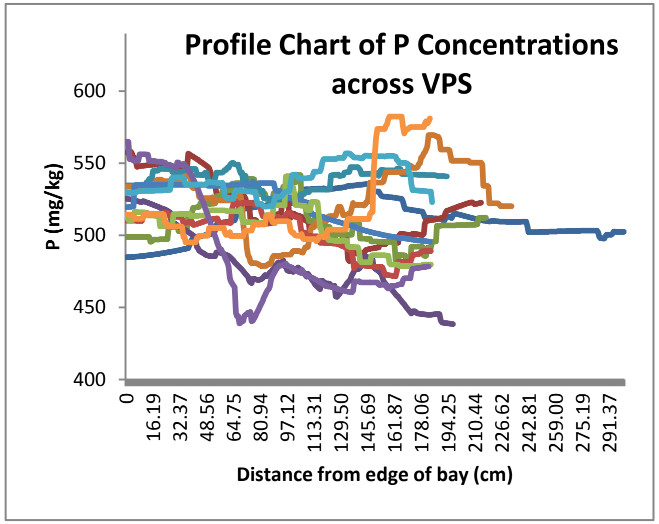

Figure 72 P (mg/kg) across the VPS

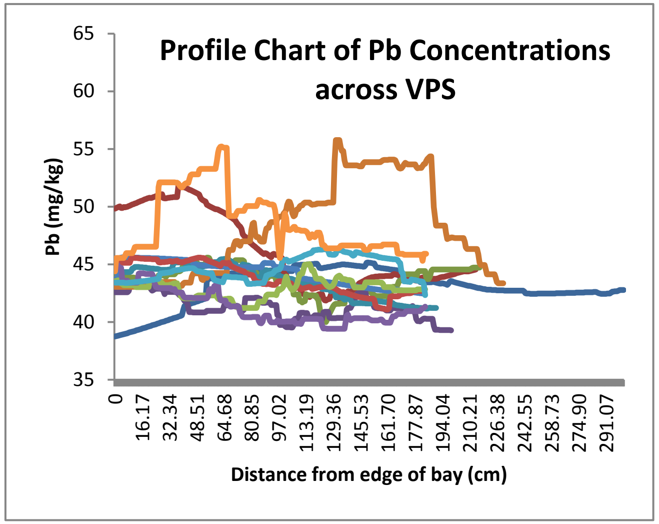

Figure 73 Pb (mg/kg) across the VPS

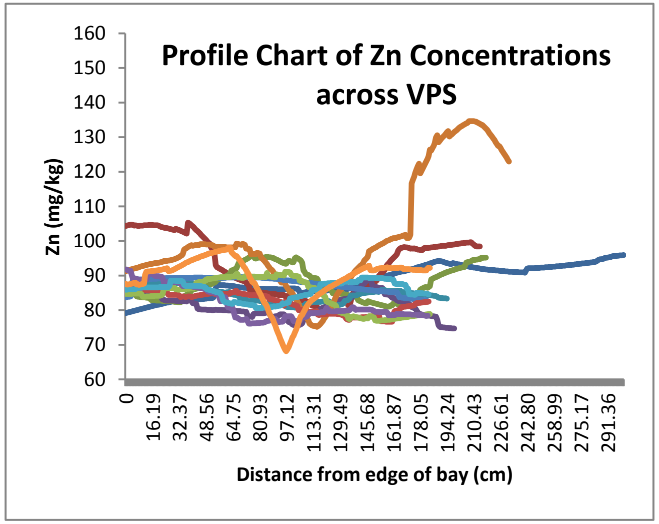

Figure 74 Zn (mg/kg) across the VPS

Both forms of data presentation (kriging and profile charts) provided visual representation of distribution trends of element concentrations across the VPS.

5.7 Overview of Field Trial Results

Oil application to compost to determine grass growth inhibition in a pot trial did not take into account the effects that vehicles would have on a VPS, thus the research was expanded to field trial, allowing these effects to be analysed. With no possibility of installation of a VPS at Coventry University, five regularly-used, grass-covered bays located at a primary school in Kenilworth, Warwickshire, were subjected to geochemical, magnetic and GIS analyses.

PCA cluster charts and associated dendrograms identified that investigated variables were split into two main clusters that represented the majority of the variance: geochemical variables and magnetism variables. With exception of Bay 3, compaction formed the next significant percentage of variance. Dendrograms displayed subsets of similar clusters, in addition to two main clusters. Detailed cluster subsets confirmed that Mo was detected in the magnetism cluster; PCA charts had also displayed Mo separately to other heavy metal variables. Despite the clear distinction between the magnetism and geochemical clusters by both PCA charts and dendrograms, it was not possible to state if there was a significant relationship between geochemical/heavy metals and magnetism components as the clusters overlapped (with the exception of Bay 1). Dendrograms also showed that alkali earth metals were not always located in the geochemical cluster.

Comparing compaction readings and mean element concentration data across the VPS, One-Way ANOVA revealed that all variables except Mo ($P = 0.476$) displayed significant difference in their means in comparison to the control samples. These results indicated that vehicles parking on the VPS bays had a significant effect on the variables.

Despite statistical analyses determining that Mo had no significant difference in mean sample concentrations in comparison to control samples, hot spots of Mo concentrations were determined using Kriging (Figure 61, Page 150). However, the concentrations at these hotspots were minute, with maximum concentrations of 0.06 mg kg^{-1} detected. Considering that 5% of the parking surface was analysed and the majority of these soil samples did not register Mo detection with geochemical analysis, any samples that did indicate small concentrations of Mo would appear as hot spots. To be certain that these 'hot spots' were genuine, analysis of all possible sampling locations (rather than a selection across the VPS) would identify if Mo concentrations were truly elevated. Statistical analyses would then confirm whether Mo mean concentrations were significantly different to control means.

One-Way ANOVA did not specify differences between individual sampling locations, thus data was subjected to Two-Way ANOVA with Tukey Multiple Post-Hoc Comparison. Control, non-parked area data was significantly different to the parking bays, with Bay 1 compaction data significantly different to Bays 2-5 (which did not differ significantly with each other). This data coincides with questionnaire responses, which indicated that car park users were more likely to park on Bays 2-5 as they were easier to drive onto (see Section 5.5). Significant differences were shown in most of the elements analysed. Elements that displayed no significant difference in sample means between control and bay data were Mo, P and Zn. Bays 2 and 5, and Bays 3 and 5 showed significant difference in mean concentrations for Cr and Cu respectively, with remaining elements highlighting significant differences between multiple bays (as shown in Table 28).

Boxplots provided an additional graphical display of the differences in data comparison. A compaction boxplot presented three distinct patterns. Data from the control area and Bay 1 displayed greatest variation in compaction. Most data was represented by the box and whiskers, thus showing few extreme outlier data. Bays 2 and 3 showed little variation in compaction (majority of values displaying high compaction readings), with outliers displaying data of less-compacted areas. Data from Bays 4 and 5 displayed no variation in compaction, indicating that with the exception of the few less-compacted outliers, the bays had compacted surfaces. These boxplots reinforced results from the Post-Hoc Comparison and parking habit questionnaires completed by car park users, showing that greater compaction and less variation in data occurred in bays which were further away from the control, non-parked area.

Applying boxplot comparison to element concentrations, the majority of element means displayed positively skewed data in samples taken from the parking bays (Table 29), indicating that mean concentrations were increased in comparison to the control samples. However, Cu displayed negatively skewed data in Bays 1-4 in comparison to Bay 5 and control samples, indicating less concentrated samples across this section of the VPS.

In anticipation of using magnetism parameters as a proxy to determine sample pollutants, the relationships between χlf and mean element concentrations were investigated. Little correlation between χlf and element concentrations (Table 30), with greatest correlation shown by Bay 1 Cu sample concentrations (R^2 = 0.087). Most bays showed that elements had no linear correlation with χlf, thus use of mineral magnetism to determine if contaminants present in this research would not be suitable as an alternative method, despite previous research demonstrating good associations (Lu *et al*. 2006; 2007; Yang *et al*.

2007; Blaha *et al*. 2008; Lu, Blundell *et al*. 2009; Morton-Bermea 2009; Wang and Guo 2010; Kim *et al*. 2010; Zhang *et al.* 2011).

From Lu, Wang and Guo (2010), the relationship between χlf and SIRM was determined for each sampling location. With R^2 values displaying significant correlation across the VPS (Table 31), slope values indicated that samples analysed from the VPS (including the control, non-parked area) contained magnetite particulates. These particulates would have arisen from vehicles parking on the surface of the VPS, with road dusts, exhaust emissions, tyre wear and brake abrasion as sources.

To reinforce data obtained from VPS soil samples, school staff that regularly used the school parking bays completed a questionnaire on their parking habits. By understanding if they used the VPS, their bay preferences and frequency of use, it was possible to determine if certain bays were subjected to more regular use and if this related to increased compaction and contaminant data. Bays 3 and 5 were identified as the preferred bays, with common reasons including the bay's proximity to the school building, ease of parking and making it easier for other to park around them. As shown in VPS data emphasising compaction and pollutant distribution/concentrations, regularity of parking may have contributed to the change in compaction and contaminant variables.

An alternative method of data presentation was chosen by use of GIS. Map layers displaying compaction and elemental concentrations were exported from ArcGIS® and created an interactive PDF file using Adobe®, allowing the possibility of turning spatial data layers on and off to provide a visual, informative method that would satisfy the aim of making this research a novel concept, following previous studies focusing on larger scales. A trend in compaction data can be seen across the VPS; compaction increased the closer the bay was to the school building. This pattern partly corresponded with questionnaire responses, where VPS users indicated their bay preferences and stating these bays were used on a more regular basis. Other sources may have contributed to compaction of the VPS surface, in addition to staff members parking their cars on the VPS. Other vehicles, such as vans and lorries may have parked on the VPS whilst making deliveries to the school, plus school visitors' vehicles utilising the spaces if asphalt alternatives were unavailable. Foot fall may also have influenced compaction data and questionnaire respondents confirmed whether they walked over the VPS as a short cut to the school entrance. Data such as this would be impossible to determine without a monitoring system (i.e. CCTV) thus these additional compaction sources can only be speculated. Mapping soil compaction at this scale has not been previously investigated, thus this research could not be compared to any studies at this scale.

Mean element concentrations across the VPS seemed to form patterns. Examining kriging and profile charts for element dispersal across each parking bay, it was possible to see that greater concentrations were mainly situated close to the edges of bays, particularly where vehicles drove onto the surface, at the edges where their tyres rested when parked, and areas which represented locations over which the engine may have rested when vehicles were parked.

The following chapter discusses results from Chapters 4 and 5 to determine if aims and objectives had been fulfilled for this research, putting the results into perspective of the impact of vehicle pollutants on a VPS. Conclusions including recommendations for VPS design, suitability of analyses and result presentation will provide proposals for additional research.

Chapter 6 Discussion

Chapters 4 and 5 presented results from the preliminary pot trial and the VPS field trial which aimed to determine pollutant tolerance and retention capabilities respectively. Understanding these characteristics made it possible to determine whether a variety of grass species could endure pollution from the presence of oil following application to compost, which in turn could establish whether they were suitable for use on a vegetative surface, for the purpose of parking. Scaling up the research from pot trial to field trial enabled the possibility to analyse the parking surface in more detail, establishing the effect of vehicles on a VPS by utilising additional approaches for pollutant detection and data presentation. This chapter assesses whether the aims and objectives for this research, outlined in Chapter 1, have been achieved, reflecting on the reliability of methods used and promoting recommendations for additional research.

6.1 Preliminary pot trial to analyse the effect of oil contamination on four grass species

The initial aim for this study was the determination of the effects of oil contaminated compost had on the growth of four grass species (*A. stolonifera* L., *F. rubra* L., *P. trivialis* L. and *L. perenne* L.), to investigate their pollutant tolerance capabilities. These species were used as model systems to replicate plants growing on a vegetated surface, assessing if they could satisfactorily resist the presence of oil and at the same time, play a role in the clean-up of pollutants, thus creating the primary foundations into understanding their characteristics and whether they could be applied to VPSs. Statistical analyses were used to show that as pollutant addition to the compost was increased, there was a detrimental effect on the growth of the grass varieties, in particular pots that were subjected to oil volumes of 2.5% and above. ANOVA and regression analyses provided probability values on the hypothesis (Section 4.1), in addition to cumulative growth and identification of EC_{50}, proving the theory that the presence of the contamination repressed growth, and the effect on plant growth intensified as the percentage of the contamination increased. ANOVA proved through both freshly-harvested and dried samples that grass growth in all four species had been significantly affected by the presence of oil. This data was validated through regression, with the exception of freshly-harvested *P. trivialis* L. samples obtained from Harvest 5 and dry *P. trivialis* L. samples from Harvests 5 and 6. These samples indicated that at this stage of the study, the presence of oil contaminants in the compost did not significantly affect the growth of this species.

An additional method of determining the effects on growth was undertaken by measuring the cumulating biomass produced by the grasses during the study. Cutting the shoots down to 2cm from the compost surface and weighing freshly-harvested grass biomass immediately ensured consistency in methodology for each pot. Immediate recording of the weight allowed the most accuracy of the biomass measurement, before external influences caused any effect (i.e. drying out of plant material). Data indicated that *F. rubra* L. produced the least total cumulative growth, whereas *L. perenne* L. (with the exception of Harvest 5 where *P. trivialis* L. is greater, which supports the insignificant regression results mentioned above) showed the greatest total cumulative growth in each of the oil contamination volumes. With each species, most growth occurred in control pots (0% v/w oil). Growth decreased in pots as oil concentrations increased (Chapter 4.2) with least growth occurring in *A. stolonifera* L. and *L. perenne* L. pots containing 20% (v/w) oil (no growth in *F. rubra* L. and *P. trivialis* L. 20% (v/w oil) pots).

With the knowledge that increasing oil concentrations caused inhibition in growth of the four grass species, determining the volume at which the pollutant caused an inhibitory effect in 50% (EC_{50}) of the grass shoots, determined the toxicity at which the grasses could tolerate the pollutant. With one application of oil to the pots at the start of this study (the purpose of this pot trial was to define pollutant tolerance characteristics in the species and was designed to take place over a limited duration), EC_{50} values were identified from mean grass sample weights obtained from Harvest 1. With reference to Figure 34 (Page 108), it can be determined that *F. rubra* L. required the greatest volume of oil to cause an effect in 50% of its shoots (21.25 ml), with *A. stolonifera* L. requiring 13.25 ml oil. This showed that the presence of oil contamination in compost was more toxic to *L. perenne* L. than it was to *F. rubra* L.

Previous laboratory studies by McGrath (1992), Vwioko and Fashemi (2005) and Sharifi, Sadeghi and Akbarpour (2007) supported the results produced by ANOVA and regression analyses in this study. These investigations indicated that increases in oil concentrations that were applied to the growing material stimulated a detrimental effect on germination and growth of the species. McGrath (1992) subjected *L. perenne* L. *cv*. Vigor to increasing volumes of diesel oil in soil mixtures, demonstrating that even 1g oil/100g soil caused inhibition effect. Greater volumes of oil contamination (8g and 16g/100g soil) completely prevented growth, which decreased throughout the duration of the investigation (112 weeks), with suggested causes such as biodegradation, evaporation and elution (McGrath 1992). Similarly to this study, growth in pots containing 1-10% (v/w) oil displayed reduction in biomass production, with pots containing 20% (v/w) oil producing growth in *L. perenne* L. pots only and no growth by the other species.

Vwioko and Fashemi (2005) detected delay in germination and decline in growth when they exposed *R. communis* L. seeds to increasing concentrations of used lubricating oil (1-6 % w/w) to soil. Seeds germinated much quicker in concentrations up to 3% (w/w) compared to those in 4-6% oil (w/w), yet growth was affected in pots containing oil volumes of above 1% (w/w), significantly affecting plant height, stem girth and flowering, and above 2 % (w/w) significantly affected leaf area and plant biomass. Grass shoots in this study were not measured for the physical effects that oil contamination played a part on, yet it was visually clear to establish that growth was depressed and a reduction in biomass was observed.

Subjecting a variety of six grasses (*M. truncatular*, *B. mermis, S. seral, T. sativa, A. deserterum* and *L. ussitasimum*) to increasing concentrations of used lubricating oil (25, 50, 75 and 100g spent oil/kg soil), Sharifi, Sadeghi and Akbarpour (2007) investigated growth inhibition and subjected the grasses to a phytotoxicity test. Each species displayed a dose-dependent response, demonstrating loss of biomass and growth, which were significantly different to the control grasses. The phytotoxicity test considered that PAHs in the lubricating oil may have caused an indirect secondary effect on the relationship the movement, retention and uptake of water by the plant from soil (McCauley, Jones and Jacobson 2005). Vwioko and Fashemi (2005) had suggested as part of their research that petroleum-contaminated soil may affect intra-soil relationships between roots and microorganisms which assist carbon, water and nutrient exchange, in addition to the possibility that the reduction in germination was affected by the seed surface being coated in oil. These secondary effects may be the cause of growth reduction as plants obtain their water and nutrients directly from the soil. As oil has hydrophobic characteristics, water would be repelled from roots, thus preventing the grass from receiving its requirements. Each pot in this study was watered to field capacity every two days, thus this may not have caused a problem to the grasses, in spite of the effects on their growth.

The method in which oil was added to the compost may have had an effect on the growth of grasses. Ensuring that the methodology of the trial was consistent, McGrath (1992) homogenised soil mixtures following application of oil, before sowing seeds on the surface. This ensured that seeds were subjected to the contamination. Application of oil to the compost in this study was also mixed to maintain consistency. However, this method would not simulate oil drips onto a VPS from a leaking engine. Dripping the required volume of oil onto the compost surface from an elevated location would simulate engine oil leaks; however, despite imitating an engine leak, this method would not ensure that all grass shoots and seeds would be subjected to the pollutant, as the contamination would be localised. Additional limitations, including application of oil and its mobility in the compost, will be mentioned later in this chapter.

6.1.1 Element distribution in grass and compost

Research on *P. virgatum, F. arundinacea* and *C. cajan* demonstrated that it was possible for plants to withstand the presence of oil in soil, even if growth was affected (Vavrek and Campbell, 1999). Vwioko *et al.* (2006) also demonstrated that *R. communis* L. possessed the ability to factors Mn, Ni, Pb and V in significant amounts in comparison to control soil samples, when grown in soil contaminated with used lubricating oil. This resulted in Vwioko *et al*. (2006) stating that *R. communis* L. was capable of removing metals from soils. With these investigations in mind, a supplementary pot trial was conducted to determine whether elements could accumulate in grass biomass and compost, which may aid retention of pollutants if forming part of a VPS. Seel (2006) observed that mean concentrations for Ca, Cu, K, Mg, Mo, P and Zn in grass samples were significantly affected subsequent to oil application. However, this outcome was not replicated by element concentrations in compost samples, with no significant concentration influence. Waite (2010) also investigated heavy metal (Cd, Cu, Ni, Pb and Zn) concentrations in compost and grass samples, following growth in street dust contaminated compost. Similarly to Seel (2006), Waite (2010) determined that heavy metal concentrations were not enhanced in root nor compost samples, yet in comparison, grass shoots showed significant concentrations. Both studies identified that element concentrations in compost were not significantly affected by the presence of oil contamination. Either elements were accumulating in grass biomass or microbes in the compost were aiding their 'removal'. Work by Coupe *et al*. (2005) identified element constituents that had enriched used engine oil (either through engine wear or via addition for optimal oil performance). Coupe *et al*. (2005) concluded that oil nutrients may perform as a principle oil degrader to biodegradation-stimulating microbes, leading to the idea that this may influence microbes in the compost, thus a reason for insignificant element concentrations in the compost.

If microbes can degrade oils in soils and a variety of plants have the ability to accumulate elements in their biomass, their use in VPS would make this type of SUDS a successful method of pollutant control. With both *F. rubra* L. and *L. perenne* L. demonstrating best results in toxicity to oil contamination and biomass production in the experimental period respectively, these species would make ideal candidates for trial in VPS.

Both the idea of producing a laboratory-based growth media testing desired oil concentrations and the study of oil treatments to pots may provide a basis of what could happen to the growth of grass in the event of an oil leak, these investigations would not take into account that the surface of a VPS would also be subjected to heavy metal contamination, vehicle emissions and atmospheric pollutants, not to forget the impact compaction would have on the surface. This highlights the need for scaling up the research, thus analysis of a VPS would attempt to provide this additional data that would be a result of day-to-day usage of a vegetated car park.

6.2 Compaction, Geochemical and Mineral Magnetism Analysis of a VPS

Investigating growth inhibition effects of oil contamination on a variety of grass species not only increases the understanding of the different characteristics each possesses, but it also provides an essential basis on which species is suitable for use in a vegetated SUDS. Many studies, including those cited in Chapter 2, have focused on pollution of vegetated locations that have been subjected to anthropogenic sources. Detailed investigations of vegetated surfaces in parking use have primarily focused on water quality and storm-water management (Gomez-Ullate *et al.* 2010a; 2010b). This study investigated the effects that vehicles have on a VPS, with the aim of determining changes in surface compaction in relation to bay usage and the dispersal of vehicle and anthropogenic elements across the parking surface, the latter utilising geochemical and mineral magnetic techniques.

6.2.1 Compaction and Geochemical Analysis of a VPS

Bond (1999) identified that cars leaked on average 200mg of oil per square meter each week onto a typical car park surface, equating to approximately 120g per year per bay. Despite being seen as a low level of contamination at the time, accumulation of contamination would occur over a period of time. If this build-up was not captured by an interceptor such as a vegetated surface, contaminants would contribute to pollution once drained from source via traditional drainage. With previous literature identifying the ability of vegetated surfaces to accumulate pollutants (see Chapter 2.3) and the capability of plants to uptake elements from soil (Seel 2006; Vwioko *et al.* 2006; Waite 2010), installation of a VPS to capture contaminants and to use plants as a method of pollutant removal from the soil, presents a novel study on the physical characteristics of a VPS.

Compaction and mean element concentrations were analysed using ANOVA and boxplots, to determine the relationship between non-parked control samples and changes in concentrations identified across the bays. ANOVA determined significant differences between the control and the bays regularly parked on, with the exception of Mo. As the least abundant trace element in soil (Nutrient Advantage 2003), concentration levels of Mo were not expected to alter much, particularly now that vehicles are rarely constructed from steel (Mo being primarily used as an alloying agent in this metal) (Gagnon n.d.). Elevation of element concentrations across the VPS corresponded with previous literature that investigated element dispersal influenced by vehicle emissions and traffic density. Table 34 displays just a few of the studies that focused on pollution in roadside vegetation, identifying that increased concentrations were influenced by road runoff and vehicle pollution.

Table 34 Brief summary of roadside vegetation pollutant studies

Author	**Elements analysed**	**Source / location**
Ramakrishnaiah and Somashekar (2002)	Pb, Zn, Cd, Ni, Cu, Cr and Mn	Traffic emissions / roadside locations in Bangalore
Nouri and Naghipour (2002)	Cd, Cu, Ni, Pb and Zn	Slow traffic jams, repeated braking, emissions from standing traffic / highways in Tehran
Akbar *et al.* (2006)	Cd, Cu, Pb and Zn	Roadside soils / different verge locations
Shaikh *et al.* (2006)	Cd, Pb, Cu and Zn	Vehicular emissions / highway in Botswana
Jankaitė, Baltrėnas and Kazlausklenė (2008)	Ni, Cu, Cr, Pb, Zn, and Mn	Vehicular emissions / roadside soils of highways in Lithuania

These investigations mainly focused on changes in heavy metal concentrations with distance from the source location, indicating that mean heavy metal concentrations decreased the further the distance from the source. Ramakrishnaiah and Somashekar (2002) also determined that concentrations of heavy metals decreased with depth, indicating that the surface of vegetation captured and limited migration of the metals through the profile of the soil. The study of the VPS in this research investigated the concentrations of a variety of elements from the surface of the vegetated parking bays. The section of the VPS utilised for control samples was located next to the road and to the main gate providing access to the school car park. Despite the location of the control area, element concentrations from bays that were regularly parked on displayed significant increases in comparison to control samples. Bearing in mind literature that researched pollutant concentrations from roadside locations (including those in Table 34 and in Chapter 2.3), it was considered that samples obtained from the control location may have been influenced by emissions from passing traffic. However, this literature focused on locations that were subjected to high densities of passing traffic (highways), or at junctions or locations where vehicles were long-standing due to light controls or traffic jams. Clinton Primary is located in a residential estate where passing traffic is for residential properties or deliveries for local shops. Traffic intensity in comparison to previous studies mentioned in Chapter 2.3 is light, thus there is little passing traffic to contribute an 'external' pattern. Taking this into consideration, changes in mean element concentration across the VPS is more likely the result of vehicles parking on the surface (in particular heavy metals and particulates from tyre, brake and road dusts (Adachi and Tainosho (2004)) or from atmospheric influence. Kriging and profile charts produced in GIS provided a visual representation of element dispersal across the VPS. As changes in contaminant concentrations were more likely to result from vehicles parking on the surface, graphical illustration provided the simplest method of determining possible relationships in the data (see Chapter 6.3).

Subjecting compaction, geochemical and mineral magnetism data to PCA, variables were clustered into similar factors. Two main clusters identified factors relating to geochemical and magnetism variables, with compaction located with the magnetism cluster. Use of cluster charts and dendrograms provided visual representation of the data, confirming the possibility that the geochemical and magnetism factors may not have a significant relationship.

6.2.2 Mineral Magnetism Analysis of a VPS

Use of geochemistry to determine contaminant concentrations in soil samples required an invasive form of analysis. Previous studies (Table 35) have successfully used mineral magnetism to characterise heavy metal concentrations in soil samples, as it has been found to provide a quick and non-destructive method of quantifying contaminants (Charlesworth and Lees 2001). Lu *et al.* (2005), Lu, Bai and Xue (2007), Morton-Bermea (2009) and Kim *et al*. (2010) demonstrated positive correlation between metal concentrations and χ, suggesting that χ could provide a reasonable tracer of heavy metal contamination.

Table 35 Brief summary of studies investigating the use of mineral magnetism for heavy metal contamination determination

Author	**Heavy metals showing correlation with χ**	**Location / source**
Lu *et al.* (2005)	Cd, Cu, Fe and Pb	Inner wall of exhaust pipe
Lu, Bai and Xue (2007)	Cd, Cr, Cu, Fe, Mn, Pb and Zn	Urban topsoils from industrial areas and roadsides
Morton-Bermea *et al.* (2009)	Cr, Cu, Fe, Ni, Pb, V and Zn	Urban soil samples
Kim *et al.* (2010)	Cd, Cr, Fe, Mn, Ni, Pb and Zn	Compared forest samples with industrial roadside and abandoned mine soils

Studies by Charlesworth *et al*. (2001), Zhang *et al*. (2011) and Zhang *et al*. (2012) have shown different relationships between heavy metals and magnetic parameters. Charlesworth *et al*. (2001) identified inconsistent correlation between heavy metals and magnetism in sediment samples from two Coventry pools, whereas Zhang *et al*. (2011) detected good correlation in river sediment samples, in particular heavy metals and SIRM. Investigating street dusts, Zhang *et al*. (2012) established that elements resulting from PCA were divided into two Groups: Group 1 elements (Nd, La, Sm, Ce, Tb, Rb, Cs, Eu, Ba) had significantly negative correlation with magnetic parameters (element source: erosion and weathering of parent rock) and Group 2 elements were split into three subgroups in their correlation with magnetic parameters M_s, χ and SIRM (Table 36):

Table 36 Group 2 elements and their anthropogenic sources (Zhang *et al*. 2012)

The studies listed in Table 36 may have shown positive correlations between heavy metals and χ. However, in comparison with correlation coefficients determined between geochemistry and χ in this study, it was shown that a relationship was only present in four of the sampling locations (see Chapter 5.4.1, Table 30), indicating low correlations with Cu (Bay 1: R^2 = 0.087), P (Control and Bay 1: R^2 = 0.061, R^2 = 0.055 respectively) and Pb (Bay 2: R^2 = 0.072). Studies that identified strong positive correlations had obtained samples from areas yielding anthropogenic pollutants (industrial areas, roadsides, sediment close to a Fe-smelting plant) The VPS samples came from a residential location with little passing traffic, thus the vegetated surface would not been subjected to such pollutant amounts as those in the studies identified.

An additional mineral magnetic approach, also used as an alternative indicator of heavy metal pollution in soil samples is the relationship between SIRM and χ. Lu *et al*. (2006; 2007), Yang *et al*. (2007), Blaha *et al*. (2008) and Lu, Wang and Guo (2010) identified good relationships with these magnetic parameters and heavy metals. Analysing the relationship between SIRM, χ and soil samples from the VPS identified that despite displaying low concentrations of pollutants, SIRM/χlf ratios suggested the presence of SD and MD magnetite, which could possibly have influenced by pollutants from road dusts, exhaust emissions, tyre wear and brake abrasion. Research by Yang *et al*. (2009) emphasised that road dusts containing magnetite indicated that polluted samples were a result of anthropogenic sources (Fialova *et al*. 2006; Magiera *et al*. 2006), thus implying that mineral magnetism could be used for pollutant detection. In comparison to these studies, samples from the VPS exhibited SIRM/χlf ratios that suggested SD and MD magnetite (Table 32/Figure 48), indicating that these ferromagnetic minerals are likely to be the result of emissions and vehicle wear, and implying that mineral magnetism may be suitable as a proxy for pollutant detection.

Looking at the relationships between χlf and element concentrations, and SIRM and χlf for VPS soil samples and relating to previous studies, it may be possible to detect Cu and Pb concentrations using mineral magnetism. Confirmation of this would require further investigation, ideally with the opportunity to assess VPSs which have been subjected to greater volumes of traffic and other anthropogenic sources so a full investigation into the use of mineral magnetism on VPS samples could be undertaken.

6.3 Data Presentation using GIS

The final section to this research was to present the data using Geographical Information Systems (GIS) in an alternative approach. As previously mentioned in this study, many investigations using GIS as a form of analysis have focused on scales usually covering cities, regions or countries. Obtaining a topography layer from EDINA Digimap® provided a starting point to constructing the map, however, missing details such as the VPS location needed to be included manually. Using a GPS handset, the location of the VPS was determined and parking bays were included on the topography layer as polygons. Utilising individual cells from the SCS Integra reinforcement blocks as a template made individual sampling locations easier to determine. Each location was given an x, y coordinate thus location of each sample could be mapped, creating features of information for evaluation. Data from analyses of the VPS were added as 2D layers to the map. Identifying that individual points were difficult to interpret, data was transformed into 3D to make the information distinguishable.

As mentioned in Chapter 2, previous literature documenting spatial relationships of heavy metals (Table 37) or on studies of environmental compaction have focused on large scale areas.

Table 37 Summary of literature investigating the spatial relationships of heavy metals, using GIS technology

Author	**Heavy metals**	**Location**
Li *et al.* (2004)	Cu, Ni, Pb and Zn	Roads, at junctions and around industrial areas
Zhang (2006)	Cu, Pb and Zn	City centre, built-up residential areas and along major roads
Lee *et al.* (2006)	Cd, Co, Cr, Cu, Ni, Pb, Zn, Al, Ca, Fe, Mg and Mn	Soil pollution samples from parks and suburbs, identifying locations of high traffic
Chang *et al.* (2009)	Fe, Pb and Zn (in road dusts); Cr, Cu, Fe, Pb and Zn (soil samples); Cu, Cr and Ni (road intersection)	Road dusts and soil samples from a steel plant

Previous literature concerning compaction of surfaces has mainly focused on agricultural land as compacted soil does not support an effective growing environment for crops, reduces crop yields and leads to degradation of soil quality by runoff and soil structure destruction, restricting root penetration and soil aeration (Duiker 2002). However, mapping compaction of soil from a VPS at such a small scale has not been previously undertaken, thus this research could not be compared to any other studies at the same scale.

Rooney, Norman and Stelford (2001) utilised a penetrometer to supplement their compacted land data obtained by soil core sampling. A field trial investigated compaction of a recently-harvested cornfield, which had revealed a compacted section in the centre of the field which regularly "ponded" following sufficient rainfall. Using GIS to map compaction data obtained by the penetrometer, it was possible to assess the depth of the compacted area and allowed determination of the depth of tillage required for preparation of the land for the next growing season. According to Rooney, Norman and Stelford (2001), use of the penetrometer provided a more efficient method of analysing land compaction than with soil sampling alone. Compaction data obtained from the VPS only analysed the soil surface unlike compaction depth determined by Rooney, Norman and Stelford (2001), as the VPS was reinforced with SCS Integra blocks which supported vehicle weight, preventing rutting of the surface.

Analysing three crop management systems, Meijer and Heitman (2010) investigated agricultural traffic patterns to determine field areas that were trafficked during field operations. Establishing paths taken by each vehicle using GPS and mapping routes in GIS, Meijer and Heitman (2010) identified that up to 85% of the fields' surface areas had been driven on at least once. These data corresponded with other studies by Soane, Dickson and Campbell (1982) and Botta, Becerra and Toum (2008) which found that in many cases, the first pass of the machinery caused most compaction. With sections of the fields driven over more than once, this helped to limit the amount of compaction occurring, confining the effects to smaller areas. Using GPS and GIS to determine these effects, Meijer and Heitman (2010) recommended methods to limit compaction, creating better environments for farming. Wiatrak, Khalilian and Henderson (2009) researched soil compaction, investigating different types of soil and tillage systems that may help improve soil management. Measuring compaction between rows of corn in soils ranging from sandy to clay, using three different tillage systems, they used GPS and GIS to identify that compaction had been influenced by the type of soil, as well as the tillage method.

Previous GIS studies, including Li *et al.* (2004), Zhang (2006) and Lee *et al*. (2006) have analysed the distribution of heavy metal contamination, usually covering large areas, including city, regional or country scale. Studies by Cattle, McBratney and Minasny (2002) and Chang *et al*. (2009) assessed contamination of urban areas, using kriging and spatial analysis to map results. Detecting Pb contamination in Sydney urban topsoil to determine if locations were considered 'clean' or 'contaminated', and identifying heavy metal concentrations in road dusts and associated soils from industrial areas respectively, both studies identified elevated contamination levels which resulted from anthropogenic activities. Dao, Morrison and Zhang (2010) studied the effects of vehicle pollution on soils samples taken from a sports ground. At a slightly larger scale than the VPS, this research provided the closest comparison of scale to the present study. Dao, Morrison and Zhang (2010) analysed spatial variation utilising kriging in Al, Ca, Ce, Co, Cu, Fe, K, La, Li, Mg, Mn, Na, Ni, P, Pb, S, Sc, Sr, Th, Ti, V, Y, Zn concentrations at a roadside sports ground. A resulting map identified little variation between Cu, Pb and Zn and indicated high levels of pollution at a non-hedged roadside location of the sports ground, influenced by local traffic. They suggested planting hedgerows or erecting low walls to shield against pollution from traffic. In comparison, Clinton Primary VPS displayed lower element concentrations in the control section of the VPS than the parking bays, despite it being located close to the roadside, meaning dispersal of pollutants across the surface would have been a result of vehicle contact with the VPS, rather than via vehicle emissions solely.

Using GIS technology to map locations of contaminant concern, use of GIS maps in these studies made invaluable information easy to obtain and monitor through the analysis of spatial data. Applying this technology to a GIS map of the VPS makes interpretation of compaction and element dispersal easier to determine.

Comparing the compaction layer (Figure 54) with element layers in the form of kriging (Figures 55-64), it was difficult to see a pattern between the data, specifying relationships. Compaction and element concentration data for each bay seemed to slant from right to left across the surface. With reference to the compaction layer, the main cause for this is likely to result from VPS users parking their vehicles at an angle in the bay. The layout of the bays on the VPS made vehicle positioning difficult, particularly if asphalt bays opposite the VPS were occupied. Referring to the element kriging layers, concentrations represented across each bay were possibly influenced by the sampling locations, rather than element dispersal. With elevated concentrations also evident where vehicles drove onto the bays, it could be hypothesised that these areas of the bays were influenced by pollutants resulting from road dusts, brake abrasion and tyre wear. Ideally, if soil from each reinforcement cell had been sampled and analysed rather than relying on interpolation data resulting from kriging, dispersal data would be exhibited more accurately.

Profile charts displaying concentrations provided additional interpretation of element dispersal across the parking bays (Figures 65-74 and Appendix IIE). It was possible to see that increases in concentration on the charts correlated with kriging layers for each element, however, kriging provided a clearer representation of the changes in concentrations.

As specialist software, ArcGIS is unlikely to feature outside of establishments that use it in the field. To make the interactive map available, layers were exported to a .pdf document, making the data accessible to non-ArcGIS users (please see attached 'Additional

Appendices' disk at the back of this document). Using the layers tab on the left-hand side of the document, it was possible to activate layers of interest using the 'open eye' icon, thus enabling the possibility to compare data.

6.4 Implications of the research

The previous sections identified the immediate implications of this research. Theoretically, SUDS are designed to equally consider water quality, water quantity and amenity and wildlife, as seen in the SUDS triangle concept (see Figure 1, Chapter 1.1). SUDS are a practical application, which are designed to consider long term environmental and social factors regarding drainage, incorporating a number of interconnecting SUDS (SUDS Treatment Train) to improve water quality, quantity and amenity. Considering results from the field trial, this section considers suggestions for design and implementation of VPS use, concluding this research as a worthy study.

When designing and implementing SUDS, it is essential to ensure that the SUDS structure is located as close to the stormwater source and provides a holistic approach to pollutant treatment and management through sedimentation, filtration and biological degradation. The VPS at Clinton Primary School was site-specific; the study concentrated on the trapping and filtering of pollutants infiltrating the vegetated surface, which would in turn, enhance water quality. The vegetated surface of the Clinton Primary School VPS had been planted with a single grass species, *L. perenne* L. The planting of a monoculture on the surface is not usual practice; a mixture of species would not only provide erosion control and surface coverage, but would also maintain durability of the surface, reducing risk of plant death which would lead to surface replacement. The most appropriate coverage of a VPS would consist of a mixture of grass species, examples such as the grass mixtures suggested by

Hewlett, Boorman and Bramley (1987) in Table 4 (Chapter 2.2). This would ensure that attributes of surface coverage, cumulative growth, oil tolerance and element accumulation complement each other, combining the best points of the grass species and leading VPS surface that provides surface stability, contamination control plus an aesthetically-pleasing appearance.

Similarly to permeable paver block systems, VPSs would be ideal for applications such as residential purposes, overflow car parking, verges or access roads, as they are restricted in the amount of usage and vehicle weight that they can manage. Providing a surface and a sub-base that act as a chemical filter, whilst allowing air and water to pass through the soil and designed to distribute vehicle weight to help prevent soil compression, VPSs offer an alternative permeable surface for which authorities and planners may utilise as a 'green' aspect in their developments.

When sowing grass seed on the VPS, particularly in reinforcement blocks such as SCS Integra 500 (as installed in the Clinton Primary VPS), the surface would require a good quality topsoil and fertiliser to ensure sufficient grass growth [Source Control Systems Ltd. n.d.]. Using a quality soil would promote good root growth for stability of the grasses in the VPS, encouraging the development of a healthy and aesthetically-pleasing surface.

Reviewing the methodology adopted for this research, several strengths and weaknesses were identified and are listed in this section.

Determining the effects that oil application had on grasses and compost by use of pot trials provided a successful method of analysis. Used oil contained many pollutants that are found in vehicle component wear and emissions, thus these trials enabled the detection of biomass production and element accumulation in controlled conditions without the possibility of polluting the environment. Establishing which grass species best tolerated the presence of oil contamination enabled the research to be developed to field site scale, so inclusion of element distribution and compaction of the grass surface could be determined.

The Clinton Primary VPS was located on a small car park site and consisted of vegetated five bays; a manageable size for this research. The surface reinforcement block cells divided the surface into evenly-sized sections; each cell was labelled for sample identification and location, and the addition of coordinates to each cell enabled the samples to be mapped using GIS. Utilising GIS to create an interactive map of the pollutant distribution and compaction of the vegetated surface presented an alternative method of displaying results from the research. The software offered the possibility to those not familiar with statistical analyses the ability to visually examine data, providing comprehensible explanations on the relationships between factors affected by the pollutants which had resulted from vehicle emissions and degradation. An additional benefit of cataloguing each cell with coordinates offers the possibility of supplementing and editing data, and the potential to utilise the data in other geographical systems. Inclusion of coordinates enables datasets to integrate with global frameworks at any given point on the Earth's surface, making data accessible to those wishing to utilise it.

Utilising ICP-MS to geochemically analyse samples provided an accurate method of determining element concentrations in soil across the VPS. Mineral magnetism was also considered for pollutant detection due to its rapid and non-invasive technique. However, despite identifying that pollutants were present in samples, mineral magnetism could not distinguish element identification and concentration, thus was not considered as a suitable proxy for geochemical analysis.

In ideal circumstances, compaction data and surface samples from the VPS would have been recorded and obtained as the VPS was installed, providing baseline readings for comparison with data recorded at a later date. This would have been particularly important as the location from where the topsoil that refilled the parking surface was unknown, and pollutant content may have been influenced by its source. The VPS was in use for approximately a year prior to analysing the surface, thus compaction and element distribution would have already been influenced by parking in the bays. Installed by the local County Council, the main aim of the VPS installation was to prevent surface damage to the lawn outside the school reception, as vehicles using it for overflow parking when the remainder of the car park was full. Installation design did not include the possibility to analyse water quality and quantity which had filtered through the surface nor the use of a mixture of grass species for optimal surface coverage, thus the VPS features solely provided a reinforced surface with the aesthetic attribute of a vegetated surface.

Following the selection of vegetative species for a VPS, the ability to analyse resulting water quality following the migration of stormwater through the vegetated surface would have provided answers to whether the design of the parking surface is suitable for pollutant control. Obtaining water samples filtered by the Clinton Primary VPS was not possible, as the reinforcement blocks containing the vegetated surface had been directly installed on the soil sub-base. Installing a sub-base with water storage capacity and the ability to access the storage would permit water sample collection for quality analysis.

Surveying the Clinton Primary staff provided an overview of their parking habits and VPS usage. A better understanding on bay usage would have been gained if all visitors (including delivery drivers, parents and governors) had completed the survey. Ten respondents completed the questionnaire, yet more responses would have provided additional data for analysis.

Despite the completion of surveys, it was not possible to determine how regularly vehicles were parking on the VPS bays, nor how long the vehicles remained in the spaces per day. Overcoming this issue would either have required school staff to have monitored and recorded vehicle movement, or installation of a monitoring system (e.g. CCTV or a pressure sensor in the bay surface). Both ideas were unsuitable; monitoring the site would take up valuable time of school staff, and the latter would have required financial provisions and regular maintenance/data downloading. If the regularity of vehicles' parking on a VPS was to be recording using technology, this would need to be integrated from the outset to ensure a full collection of data.

A final weakness of the research was shown in the collection of soil for investigation. Samples were randomly selected across the VPS, selecting 5% of the surface to extract and analyse. For more accurate results on element dispersal and emphasised hotspots, analysing more samples (ideally the full VPS) would overcome this limitation; however, time and resource constraints restricted this.

6.5 Chapter Conclusion

This chapter has highlighted data that has aimed to address the research proposals, identifying previous studies that have validated ideas on the suitability of contaminant-tolerant species, methods and limiting factors. The final chapter brings this research to a conclusion, summarising findings and providing ideas for further study.

Chapter 7 Conclusion, Limitations and Further Studies

Reviewing key conclusions from the laboratory and field trials, this chapter summarises the main findings of the study. Referring to results in Chapters 4 and 5, recommendations were made on grass species suitability for use in VPS, and whether geochemical, mineral magnetism and GIS provided appropriate methods of VPS analysis.

7.1 Conclusion of the preliminary pot trial

The laboratory pot trial examining the application of used engine oil to compost identified significantly repressed growth of four grass species (*A. stolonifera* L., *F. rubra* L., *L. perenne* L. and *P. trivialis* L.), particularly in pots containing 2.5% (w/v oil) and above. ANOVA and regression analyses confirmed growth suppression, and quantifying biomass production by each species identified that *L. perenne* L. produced greatest cumulative growth during the six-month investigation. The dose-responsive effect of oil contamination on grass growth proved to be visually evident, thus the volumes of oil that were required to have 50% effectiveness in the species (EC_{50}) were determined. *F. rubra* L. displayed greatest tolerance to oil contamination, with an EC_{50} value of 8.5% (v/w), whereas despite demonstrating greatest cumulative growth during the investigation, *A. stolonifera* L. required only 5.3% (v/w) oil contamination, therefore showing more susceptibility to toxicity.

Supplementary to the data produced by the pot trial, an additional pot trial determined that Ca, Cu, K, Mg, Mo, P and Zn concentrations significantly accumulated in grass biomass at first harvest only. Element concentrations in compost did not appear to be significantly influenced by the addition of used oil to compost throughout the duration of the pot trial. Overall, the presence of oil in compost did not have a significant effect of mean element concentration in grass and compost samples. These results suggest that a VPS with grasses investigated in this research and the accompanying study of element accumulation in grasses and compost may tolerate contamination resulting from vehicle wear and tear (i.e. rusting, brake abrasion, tyre deterioration) and exhaust emissions.

7.2 Conclusion of the VPS trial

A vegetated car park was analysed to determine the effects that vehicles had on the parking surface, and GIS was used to visually display results in addition to statistical analyses. Compaction data exhibited greater compaction in surface of parking bays closest to the school building and less compaction in bays that were located near to the entrance of the car park. Soil samples were randomly selected from 5% of the surface and were subjected to geochemical and mineral magnetism techniques, resulting cluster charts and associated dendrograms identifying that variables were split into two main clusters that represented the majority of the variance: geochemical variables and magnetism variables.

One-Way ANOVA revealed that all variables except Mo displayed significant differences in their means in comparison to the control samples, thus vehicles parking on the VPS bays had a significant effect on the variables. Tukey Multiple Post-Hoc Comparison expanded compaction and element concentration differences between the sampling locations:

- mean compaction readings for the control area of the VPS were considerably lower than the parking bays; mean readings for Bay 1 were substantially lower than Bays 2-5.
- significant differences in mean element concentrations (Al, Ca, Cr, CU, K, Mg, Pb) across VPS in comparison to the control, non-parked area, with no significant difference between control and Mo, P and Zn samples.

Boxplots indicated the differences between variables across the VPS, displaying skewness of the data that confirmed differences in mean compaction readings and element concentrations. A boxplot indicating the change in compaction means across the VPS showed that the control and Bay 1 data had the most variation in data values, Bays 2 and 3 indicated little variation in compaction data, and Bays 4 and 5 displayed no variation. Indicating positively skewed data for the majority of elements, boxplots confirmed that mean concentrations increased across the VPS.

Assessing whether mineral magnetism could be used as a proxy for determining vehicle pollutants in soil samples, relationships between χlf and mean geochemical concentrations were investigated and most bays exhibited that elements had no linear correlation with χlf. Therefore, use of mineral magnetism would not be suitable as an alternative method, despite previous research demonstrating good associations (Lu *et al*. 2006; 2007; Yang *et al*. 2007; Blaha *et al*. 2008; Blundell *et al*. 2009; Morton-Bermea 2009; Wang and Guo 2010; Kim *et al*. 2010; Zhang *et al.* 2011).

With little association between χlf and element concentrations, the relationship between χlf and SIRM readings were determined for each sampling location, to conclude if samples possessed polluted materials. R^2 values displayed significant correlation across the VPS, and slope values indicated that VPS samples (including the control area) contained the presence of SD magnetite. Correlation between SIRM and χlf exhibited similarities to samples that contained magnetite, which could have been influenced by vehicles parking on the surface of the VPS (road dusts, exhaust emissions, tyre wear and brake abrasion as possible influences on these data). From these results, mineral magnetism may be suitable as an alternative to geochemistry for pollutant detection but to clearly define elements and their concentrations in samples, geochemistry remains most appropriate.

To make the results more comprehensible to understand, GIS was used as an alternative method of data presentation. By using GIS to present compaction, geochemical and magnetism data from a 5-bay VPS, provided an innovative GIS representation for research at this small scale and correlating patterns were displayed in an interactive map. A TIN layer displayed a 3D layer representation of the data which connected compaction observations, with a trend visible across the VPS; compaction increasing the closer the bay is to the school building. Kriging and profile charts displayed element dispersal across each parking bay, identifying that greater concentrations were mainly situated close to the edges of bays, particularly where vehicles drove onto the surface and in central bay areas over which vehicle engines may have rested when parked. Use of GIS to display results from the VPS provided an unconventional conclusion to this research, resulting in a comprehensible presentation of data.

Survey responses from regular users of the VPS identified parking habits. Bays 2 and 5 were most favoured, closely followed by Bay 4. Bay 1 was seen to be most difficult to use due to its proximity to the school gates (i.e. more vehicle manoeuvrability required to park on these bays).

7.3 Limitations of the research

Several experimental limitations were identified throughout the research duration and this section aims to expand on their effects on the investigations.

In terms of the *scale* of studies chosen, pot trials in the laboratory are limited as they do not represent the conditions under which the grass would naturally grow. However, laboratory studies provided a means to maintain control over some of the environmental variables such as treatment, lighting, temperature, watering. Since the growth of grasses in plant pots would not mimic that taking place in a vegetated car park environment, field scale trials were undertaken, where less experimental control could be exerted, but more natural conditions would prevail.

The effects of pollutants on individual grass species and their tolerance to oil contamination were determined on individual grass species only, the resulting data would therefore not give an indication of how the kinds of mixtures of grass varieties commonly used in vegetated parking areas (see Table 5, Page 31) would react with each other and to oil contamination. In order to investigate this, experiments would need to be extended to determine the effects of oil contamination on mixtures of a variety of grasses.

A limiting factor in the construction of the VPS was that the surface was sown with one species of grass. The VPS was installed for a year before analysis commenced, thus it was not possible to design and construct the parking surface to include a mixture of grasses on the surface. Similarly to limitations previously mentioned on the effects of oil contamination on individual grass species in the pot trial, analysing the effects that vehicles would have on a surface planted with a single species would not portray how surfaces of multiple species would react. As mentioned in Section 6.4, surfaces are usually planted with multiple species that have characteristics which complement each other in surface coverage, cumulative growth, oil tolerance and element accumulation, limiting the risk of plant death if the surface was covered by a single species.

Reflecting on the design of the field trial, a control area located away from the parking bays may have provided a better background site than the reinforced section located between the bays and the footpath/road used in the present study (see Fig 22, Page 84), since it may have been influenced by vehicle emissions from cars parking next to the control or from traffic passing the school site.

With no vegetation to protect the parking area from the road and passing traffic, aerial deposition of pollutants may have had an influence on element concentrations sampled from parking bays as concentrations appeared to increase towards the centre of the VPS, before decreasing. Locating the VPS away from the road, with added protection from trees and hedges, would have helped in limiting aerial pollutants. An example of such a car park can be seen at Kenilworth School and Sports College, where the VPS is located away from any roads, as seen on the left-hand side of Figure 75 (Stott 2010).

Figure 75 VPS at Kenilworth School and Sports College, Kenilworth (Stott 2010)

The VPS at Kenilworth School is also a larger area than Clinton Primary with 15 parking bays located off one of the main roads in Kenilworth and in addition, the site is protected by trees.

Although the questionnaire provided a useful insight into staff parking habits at the school, only ten respondents completed the survey, thus providing limited data to analyse. Ideally, extra respondents would have increased the reliability of the questionnaire. Visitors to the school included delivery drivers who parked for short periods of time; others included participants of sports clubs that took place in the evenings. Requesting the completion of questions on their use of the VPS would have provided additional data, yet would have been difficult to obtain from those not visiting the school for a long period of time. An additional limit to the questionnaire's design was that it did not take into account the length of time that the cars were parked on the VPS, so it was difficult to determine if vehicles occupied the bays for the full day. Requesting office staff to compile a list of bay usage was considered but this would have taken up part of their time. Use of a video monitoring system to screen the use of parking spaces would require preparation and specific equipment to set up, in addition to permissions from the Data Protection Act and from staff, parents and school governors. An alternative method of a detection system (e.g. detecting pressure on the surface) would also require specialist equipment and setting up during the construction of the VPS.

7.4 Further Development of VPS Study

Having investigated the effects of oil contaminated compost on the growth of a variety of grass species to determine if they could deal with possible contaminants from a VPS, followed by the examination of a currently used VPS and how vehicle affect the surface and whether pollutants can be detected using a range of techniques (geochemical, mineral magnetism), additional analyses could be applied to determine whether vegetated surfaces provide successful contaminant control.

The ability of designing and building a purpose-built VPS would be ideal for full analysis of the vegetated surface. Studies by Gomez-Ullate *et al.* (2010a; 2010b) have focused on different permeable surfaces and how they manage storm-water and pollutant control. Sufficient space to test a variety of individual grasses and grass mixtures, different soil textures, a range of reinforcement paving blocks and a variety of VPS locations (i.e. in residential and industrial locations, close to highways, in public and private locations) would present the possibilities of identifying all characteristics and variables to determine the ideal combination for best quality contamination and runoff control. A range of variables such as this may also determine whether use of mineral magnetism techniques are suitable for pollutant detection, particularly if VPSs were subjected to additional anthropogenic sources.

One factor of this study was the limited duration in which the analyses could be undertaken. Design of a long-term investigation with continuous monitoring, particularly if the VPS had not been parked on previously, could determine the effects of vehicles on a vegetated surface over a known period of time. Analysing the Clinton Primary VPS provided information on a parking area that was already in regular use, thus it was not possible to compare the surface to when the bays were first installed.

In addition to investigating different characteristics and variable, a method of monitoring use of the parking bays would enhance the comparison of control and parking bay analyses. Monitoring a VPS using installation of a system to detect the occupancy of a bay would enable observations of bay usage easier to determine and document, rather than relying on completion of a survey. A system of this sort would also be able to detect length of bay usage or the regularity of vehicles parking in the location. This would be particularly useful in the comparison with compaction and geochemical assessments.

Undertaking these further study concepts would provide supplementary detail to the data in this study, providing a more rounded investigation of the effects of vehicles and resulting pollutants on a VPS. This study has paved the way with the analysis of vegetated parking surfaces and has provided an initial indication on vegetation that may be suitable for VPS coverage and how a VPS is affected through regular use. As occurrences of VPSs increase, there is no doubt that additional studies on this type of drainage will provide supplementary knowledge to support its design and use as a successful form of pollutant control.

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Appendix I Preliminary Pot Trial

A. PEAT Microwave Program, Mars 5, 40 Vessel Carousel

Stage	Power		Ramp	°C	Hold
	Max.	%	(min)	Control	(min)
1	1200W	30	5:00	50	5:00
2	1200W	30	5:00	75	10:00
3	1200W	50	5:00	120	10:00
4	1200W	70	5:00	150	5:00
5	1200W	70	5:00	170	15:00

B. Two-Way ANOVA between Grass Species and Oil Concentration

Harvest 1 Fresh *A. stolonifera* L. Samples: ANOVA with Two Factor with Replication

SUMMARY	0	1	2.5	5	Total
1					
Count	2	2	2	2	8
Sum	22.7754	4.3014	18.733	1.9643	47.7741
Average	11.3877	2.1507	9.3665	0.98215	5.971763
Variance	11.73217	9.251021	10.063	1.304274	27.5796
2					
Count	2	2	2	2	8
Sum	19.284	10.7899	13.1349	8.6137	51.8225
Average	9.642	5.39495	6.56745	4.30685	6.477813
Variance	7.026751	0.2564	0.102197	0.623063	5.688569
3					
Count	2	2	2	2	8
Sum	22.1767	14.8229	8.3467	0.4778	45.8241
Average	11.08835	7.41145	4.17335	0.2389	5.728013
Variance	7.269103	2.319643	6.523633	0.001031	20.62035
Total					
Count	6	6	6	6	
Sum	64.2361	29.9142	40.2146	11.0558	
Average	10.70602	4.9857	6.702433	1.842633	
Variance	5.902805	8.001002	8.742459	4.139576	

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Sample	2.340535	2	1.170268	0.248674	0.783755	3.885294
Columns	245.6309	3	81.87698	17.39834	0.000115	3.490295
Interaction	75.1164	6	12.5194	2.660293	0.070397	2.99612
Within	56.47228	12	4.706023			
Total	379.5602	23				

Harvest 1 Dry *A. stolonifera* L. Samples: ANOVA with Two Factor with Replication

SUMMARY	0	1	2.5	5	Total
1					
Count	2	2	2	2	8
Sum	3.1945	0.7798	3.1152	0.2751	7.3646
Average	1.59725	0.3899	1.5576	0.13755	0.920575
Variance	0.161142	0.304044	0.573949	0.035725	0.655961
2					
Count	2	2	2	2	8
Sum	3.0394	1.6246	1.9824	1.2765	7.9229
Average	1.5197	0.8123	0.9912	0.63825	0.990363
Variance	0.139815	0.004551	0.003612	0.011935	0.147384
3					
Count	2	2	2	2	8
Sum	3.6267	2.6413	1.9115	0.016	8.1955
Average	1.81335	1.32065	0.95575	0.008	1.024438
Variance	0.140503	0.075699	0.290703	5.83E-05	0.571849
Total					
Count	6	6	6	6	
Sum	9.8606	5.0457	7.0091	1.5676	
Average	1.643433	0.84095	1.168183	0.261267	
Variance	0.106818	0.25061	0.264891	0.09817	

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Sample	0.04485	2	0.022425	0.154502	0.858519	3.885294
Columns	6.068759	3	2.02292	13.93726	0.000324	3.490295
Interaction	1.815862	6	0.302644	2.085117	0.131283	2.99612
Within	1.741736	12	0.145145			
Total	9.671207	23				

Harvest 1 Fresh *F. rubra* L. Samples: ANOVA with Two Factor with Replication

SUMMARY	0	1	2.5	5	10	Total
1						
Count	2	2	2	2	2	10
Sum	6.0121	3.5412	4.7136	3.4095	0.3983	18.0747
Average	3.00605	1.7706	2.3568	1.70475	0.19915	1.80747
Variance	0.1212781	0.297066	0.003978	0.243253	0.002499245	1.038
2						
Count	2	2	2	2	2	10
Sum	5.2564	3.984	1.8756	0.8967	0.2534	12.2661
Average	2.6282	1.992	0.9378	0.44835	0.1267	1.22661
Variance	6.962E-05	0.715926	0.0796	0.025066	0.00585362	1.080541
3						
Count	2	2	2	2	2	10
Sum	5.6404	3.5536	1.8987	0.7515	0.4678	12.312
Average	2.8202	1.7768	0.94935	0.37575	0.2339	1.2312
Variance	0.7164045	0.012928	0.472295	0.018298	2.178E-05	1.164092
Total						
Count	6	6	6	6	6	
Sum	16.9089	11.0788	8.4879	5.0577	1.1195	
Average	2.81815	1.846467	1.41465	0.84295	0.186583333	
Variance	0.1961071	0.2179	0.643789	0.503997	0.00406805	

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Sample	2.2316884	2	1.115844	6.165935	0.011108726	3.68232
Columns	23.946083	4	5.986521	33.08033	2.80046E-07	3.055568
Interaction	2.8830805	8	0.360385	1.991417	0.119077284	2.640797
Within	2.7145375	15	0.180969			
Total	31.775389	29				

Harvest 1 Dry *F. rubra* L. Samples: ANOVA with Two Factor with Replication

SUMMARY	0	1	2.5	5	10	Total
1						
Count	2	2	2	2	2	10
Sum	1.1412	0.7256	0.9467	0.6942	0.0513	3.559
Average	0.5706	0.3628	0.47335	0.3471	0.02565	0.3559
Variance	0.000933	0.016453	3.645E-06	0.012832	0.000389205	0.040975
2						
Count	2	2	2	2	2	10
Sum	0.8317	0.9144	0.3542	0.1599	0.0383	2.2985
Average	0.41585	0.4572	0.1771	0.07995	0.01915	0.22985
Variance	0.01519	0.075972	0.00302642	0.001285	0.000190125	0.045281
3						
Count	2	2	2	2	2	10
Sum	1.2004	0.7752	0.3395	0.1705	0.0549	2.5405
Average	0.6002	0.3876	0.16975	0.08525	0.02745	0.25405
Variance	0.049298	0.001191	0.000051005	0.006149	0.000266805	0.05624
Total						
Count	6	6	6	6	6	
Sum	3.1733	2.4152	1.6404	1.0246	0.1445	
Average	0.528883	0.402533	0.2734	0.170767	0.024083333	
Variance	0.020925	0.020639	0.02461502	0.022715	0.000184478	

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Sample	0.089492	2	0.044746108	3.663091	0.050649607	3.68232
Columns	0.926557	4	0.231639196	18.96289	9.86805E-06	3.055568
Interaction	0.172673	8	0.021584078	1.766957	0.162808827	2.640797
Within	0.183231	15	0.012215397			
Total	1.371953	29				

Harvest 1 Fresh *P. trivialis* L. Samples: ANOVA with Two Factor with Replication

SUMMARY	0	1	2.5	5	10	Total
1						
Count	2	2	2	2	2	10
Sum	21.2158	6.9955	14.894	11.6326	0.3921	55.13
Average	10.6079	3.49775	7.447	5.8163	0.19605	5.513
Variance	0.491437	0.628657	3.725904	0.552301	0.00456	14.4051
2						
Count	2	2	2	2	2	10
Sum	15.2039	12.9064	11.798	12.5098	0.6399	53.058
Average	7.60195	6.4532	5.899	6.2549	0.31995	5.3058
Variance	12.08599	0.430406	4.463474	0.502603	0.00456	9.209716
3						
Count	2	2	2	2	2	10
Sum	22.4218	17.3425	8.4151	0.6195	0.4927	49.2916
Average	11.2109	8.67125	4.20755	0.30975	0.24635	4.92916
Variance	1.364552	0.001676	1.230096	0.010702	0.002471	21.90147
Total						
Count	6	6	6	6	6	
Sum	58.8415	37.2444	35.1071	24.7619	1.5247	
Average	9.806917	6.2074	5.851183	4.126983	0.254117	
Variance	5.778244	5.601419	3.984074	8.994357	0.005425	

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Sample	1.752196	2	0.876098	0.515364	0.607484	3.68232
Columns	289.5812	4	72.39531	42.5865	5.11E-08	3.055568
Interaction	94.56601	8	11.82075	6.953551	0.000683	2.640797
Within	25.49939	15	1.699959			
Total	411.3988	29				

Harvest 1 Dry *P. trivialis* L. Samples: ANOVA with Two Factor with Replication

SUMMARY	0	1	2.5	5	10	Total
1						
Count	2	2	2	2	2	10
Sum	3.229	1.3053	2.4363	2.0133	0.0812	9.0651
Average	1.6145	0.65265	1.21815	1.00665	0.0406	0.90651
Variance	0.006962	0.010996	0.069751	0.0201	0.000531	0.328181
2						
Count	2	2	2	2	2	10
Sum	2.412	2.1909	2.0567	2.1237	0.0596	8.8429
Average	1.206	1.09545	1.02835	1.06185	0.0298	0.88429
Variance	0.324979	0.017168	0.069975	0.015121	0.000768	0.254339
3						
Count	2	2	2	2	2	10
Sum	3.5706	2.7729	1.7764	0.1231	0.0715	8.3145
Average	1.7853	1.38645	0.8882	0.06155	0.03575	0.83145
Variance	0.003058	0.003128	0.028608	0.007405	0.002106	0.548692
Total						
Count	6	6	6	6	6	
Sum	9.2116	6.2691	6.2694	4.2601	0.2123	
Average	1.535267	1.04485	1.0449	0.710017	0.035383	
Variance	0.137884	0.115487	0.055605	0.26144	0.000705	

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Sample	0.029733	2	0.014866	0.384038	0.687613	3.68232
Columns	7.355031	4	1.838758	47.50016	2.42E-08	3.055568
Interaction	2.245213	8	0.280652	7.250001	0.000545	2.640797
Within	0.580658	15	0.038711			
Total	10.21064	29				

Harvest 1 Fresh *L. perenne* L. Samples: ANOVA with Two Factor with Replication

SUMMARY	0	1	2.5	5	10	Total
1						
Count	2	2	2	2	2	10
Sum	29.0471	25.8813	15.8873	2.3764	1.2926	74.4847
Average	14.52355	12.94065	7.94365	1.1882	0.6463	7.44847
Variance	3.402136	39.7395	0.000471	0.036612	0.028179	41.67332
2						
Count	2	2	2	2	2	10
Sum	31.9199	16.8687	17.9976	16.5369	1.7278	85.0509
Average	15.95995	8.43435	8.9988	8.26845	0.8639	8.50509
Variance	4.856286	0.346029	1.351039	8.585954	0.00076	27.075
3						
Count	2	2	2	2	2	10
Sum	29.4588	22.1044	16.532	2.4156	0.375	70.8858
Average	14.7294	11.0522	8.266	1.2078	0.1875	7.08858
Variance	3.36E-05	1.445	5.524488	0.078646	0.070313	35.83254
Total						
Count	6	6	6	6	6	
Sum	90.4258	64.8544	50.4169	21.3289	3.3954	
Average	15.07097	10.80907	8.402817	3.554817	0.5659	
Variance	2.134341	12.40292	1.609099	15.07132	0.115232	

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Sample	10.84156	2	5.420779	1.242055	0.316853	3.68232
Columns	795.4048	4	198.8512	45.56247	3.22E-08	3.055568
Interaction	80.35758	8	10.0447	2.301526	0.078073	2.640797
Within	65.46545	15	4.364363			
Total	952.0694	29				

Harvest 1 Dry *L. perenne* L. Samples: ANOVA with Two Factor with Replication

SUMMARY	0	1	2.5	5	10	Total
1						
Count	2	2	2	2	2	10
Sum	4.525	4.1778	2.5407	0.4964	0.313	12.0529
Average	2.2625	2.0889	1.27035	0.2482	0.1565	1.20529
Variance	0.024465	1.529151	0.00029	0.000558	7.44E-05	1.043543
2						
Count	2	2	2	2	2	10
Sum	4.8354	3.0229	3.035	2.6106	0.3159	13.8198
Average	2.4177	1.51145	1.5175	1.3053	0.15795	1.38198
Variance	0.18899	0.003724	0.044283	0.179281	4.9E-05	0.626697
3						
Count	2	2	2	2	2	10
Sum	4.5358	3.456	2.8557	0.4667	0.0917	11.4059
Average	2.2679	1.728	1.42785	0.23335	0.04585	1.14059
Variance	0.008346	0.012545	0.12888	0.002643	0.004204	0.844055
Total						
Count	6	6	6	6	6	
Sum	13.8962	10.6567	8.4314	3.5737	0.7206	
Average	2.316033	1.776117	1.405233	0.595617	0.1201	
Variance	0.050568	0.377163	0.047214	0.338731	0.004174	

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Sample	0.312249	2	0.156124	1.100768	0.358039	3.68232
Columns	18.85165	4	4.712914	33.22881	2.72E-07	3.055568
Interaction	1.649514	8	0.206189	1.453755	0.253333	2.640797
Within	2.127482	15	0.141832			
Total	22.9409	29				

Harvest 2 Fresh *A. stolonifera* L. Samples: ANOVA with Two Factor with Replication

SUMMARY	0	1	2.5	5	Total
1					
Count	2	2	2	2	8
Sum	11.7162	11.0938	10.9086	6.4314	40.15
Average	5.8581	5.5469	5.4543	3.2157	5.01875
Variance	1.499566	0.057596	4.937339	2.404625	2.535345
2					
Count	2	2	2	2	8
Sum	11.3987	9.8114	9.4969	7.5924	38.2994
Average	5.69935	4.9057	4.74845	3.7962	4.787425
Variance	0.15429	0.756696	0.112006	9.68E-06	0.668898
3					
Count	2	2	2	2	8
Sum	14.4396	7.7479	6.2189	0.4593	28.8657
Average	7.2198	3.87395	3.10945	0.22965	3.608213
Variance	2.256963	0.216679	0.197632	0.000136	7.460953
Total					
Count	6	6	6	6	
Sum	37.5545	28.6531	26.6244	14.4831	
Average	6.259083	4.775517	4.4374	2.41385	
Variance	1.34099	0.776115	2.207111	3.410788	

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Sample	9.156452	2	4.578226	4.362453	0.037682	3.885294
Columns	45.1378	3	15.04593	14.33681	0.000285	3.490295
Interaction	16.92503	6	2.820839	2.687892	0.068404	2.99612
Within	12.59354	12	1.049461			
Total	83.81282	23				

Harvest 2 Dry *A. stolonifera* L. Samples: ANOVA with Two Factor with Replication

SUMMARY	0	1	2.5	5	Total
1					
Count	2	2	2	2	8
Sum	2.7361	2.3888	2.7277	1.2992	9.1518
Average	1.36805	1.1944	1.36385	0.6496	1.143975
Variance	0.169304	0.004306	0.08732	0.120148	0.153155
2					
Count	2	2	2	2	8
Sum	2.662	2.1371	2.1598	1.8742	8.8331
Average	1.331	1.06855	1.0799	0.9371	1.104138
Variance	0.013811	0.037675	0.014416	0.013415	0.034537
3					
Count	2	2	2	2	8
Sum	3.7088	1.9746	1.6419	0.08	7.4053
Average	1.8544	0.9873	0.82095	0.04	0.925663
Variance	0.114146	0.00414	0.002805	0.0002	0.492103
Total					
Count	6	6	6	6	
Sum	9.1069	6.5005	6.5294	3.2534	
Average	1.517817	1.083417	1.088233	0.542233	
Variance	0.1277	0.017935	0.079898	0.194627	

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Sample	0.216269	2	0.108134	2.23077	0.15006	3.885294
Columns	2.87404	3	0.958013	19.76347	6.17E-05	3.490295
Interaction	1.302843	6	0.21714	4.479528	0.013132	2.99612
Within	0.581687	12	0.048474			
Total	4.974839	23				

Harvest 2 Fresh *F. rubra* L. Samples: ANOVA with Two Factor with Replication

SUMMARY	0	1	2.5	5	10	Total
1						
Count	2	2	2	2	2	10
Sum	9.3639	4.0503	8.8603	3.6551	0.3956	26.3252
Average	4.68195	2.02515	4.43015	1.82755	0.1978	2.63252
Variance	0.441706	2.310605	0.00285	1.298144	0.001959	3.645335
2						
Count	2	2	2	2	2	10
Sum	10.7668	7.217	5.1592	2.1193	0.2967	25.559
Average	5.3834	3.6085	2.5796	1.05965	0.14835	2.5559
Variance	0.370488	2.022463	0.24193	0.663898	0.004278	4.175528
3						
Count	2	2	2	2	2	10
Sum	11.3941	8.3261	7.2417	0.8799	0.2932	28.135
Average	5.69705	4.16305	3.62085	0.43995	0.1466	2.8135
Variance	3.8008	0.093528	4.81E-06	0.058175	5.78E-06	5.668958
Total						
Count	6	6	6	6	6	
Sum	31.5248	19.5934	21.2612	6.6543	0.9855	
Average	5.254133	3.265567	3.543533	1.10905	0.16425	
Variance	1.13871	1.870004	0.737451	0.790594	0.001925	

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Sample	0.34994	2	0.17497	0.232039	0.795709	3.68232
Columns	99.0649	4	24.76623	32.84403	2.94E-07	3.055568
Interaction	11.03265	8	1.379081	1.828885	0.149274	2.640797
Within	11.31083	15	0.754056			
Total	121.7583	29				

Harvest 2 Dry *F. rubra* L. Samples: ANOVA with Two Factor with Replication

SUMMARY	0	1	2.5	5		Total
1						
Count	2	2	2	2	2	10
Sum	2.8964	1.9232	2.8545	1.6797	0.03	9.3838
Average	1.4482	0.9616	1.42725	0.83985	0.015	0.93838
Variance	0.024068	0.003444	0.000496	0.002224	5E-05	0.305984
2						
Count	2	2	2	2	2	10
Sum	3.3431	2.0668	1.3487	0.6744	0.0392	7.4722
Average	1.67155	1.0334	0.67435	0.3372	0.0196	0.74722
Variance	0.09044	0.223647	0.030529	0.005513	0.000216	0.403181
3						
Count	2	2	2	2	2	10
Sum	3.4526	2.5863	2.2656	0.17	0.05	8.5245
Average	1.7263	1.29315	1.1328	0.085	0.025	0.85245
Variance	0.4998	0.000929	0.000169	0.005121	5E-05	0.569581
Total						
Count	6	6	6	6	6	
Sum	9.6921	6.5763	6.4688	2.5241	0.1192	
Average	1.61535	1.09605	1.078133	0.420683	0.019867	
Variance	0.140225	0.069944	0.121404	0.120713	8.33E-05	

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Sample	0.183332	2	0.091666	1.550684	0.244258	3.68232
Columns	9.430205	4	2.357551	39.88203	7.98E-08	3.055568
Interaction	1.191815	8	0.148977	2.520199	0.058462	2.640797
Within	0.886697	15	0.059113			
Total	11.69205	29				

Harvest 2 Fresh *P. trivialis* L. Samples: ANOVA with Two Factor with Replication

SUMMARY	0	1	2.5	5	Total
1					
Count	2	2	2	2	8
Sum	11.0135	10.4724	11.5157	10.3585	43.3601
Average	5.50675	5.2362	5.75785	5.17925	5.420013
Variance	3.867815	0.026038	0.005315	0.357604	0.669085
2					
Count	2	2	2	2	8
Sum	12.3796	11.2689	10.3555	11.4933	45.4973
Average	6.1898	5.63445	5.17775	5.74665	5.687163
Variance	0.100173	0.60599	2.614956	0.670829	0.718411
3					
Count	2	2	2	2	8
Sum	10.9438	12.7426	7.7458	1.081	32.5132
Average	5.4719	6.3713	3.8729	0.5405	4.06415
Variance	0.464262	0.491437	0.10089	0.000169	5.795933
Total					
Count	6	6	6	6	
Sum	34.3369	34.4839	29.617	22.9328	
Average	5.722817	5.747317	4.936167	3.822133	
Variance	1.017537	0.490027	1.289857	6.73158	

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Sample	12.11707	2	6.058536	7.812863	0.006717	3.885294
Columns	14.75607	3	4.918691	6.34296	0.008017	3.490295
Interaction	26.22245	6	4.370408	5.635916	0.005446	2.99612
Within	9.305479	12	0.775457			
Total	62.40107	23				

Harvest 2 Dry *P. trivialis* L. Samples: ANOVA with Two Factor with Replication

SUMMARY	0	1	2.5	5	Total
1					
Count	2	2	2	2	8
Sum	3.5435	2.658	3.0703	2.9074	12.1792
Average	1.77175	1.329	1.53515	1.4537	1.5224
Variance	0.035405	0.016635	6.61E-05	0.049047	0.044296
2					
Count	2	2	2	2	8
Sum	2.98	2.8583	2.8567	3.0494	11.7444
Average	1.49	1.42915	1.42835	1.5247	1.46805
Variance	0.0021	0.025606	0.160461	0.064225	0.037993
3					
Count	2	2	2	2	8
Sum	2.8461	3.0167	2.0156	0.2237	8.1021
Average	1.42305	1.50835	1.0078	0.11185	1.012763
Variance	0.005171	0.028298	0.000707	0.000214	0.355087
Total					
Count	6	6	6	6	
Sum	9.3696	8.533	7.9426	6.1805	
Average	1.5616	1.422167	1.323767	1.030083	
Variance	0.035929	0.02057	0.094429	0.529597	

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Sample	1.253256	2	0.626628	19.38348	0.000174	3.885294
Columns	0.912267	3	0.304089	9.406385	0.001784	3.490295
Interaction	1.761437	6	0.293573	9.081089	0.000692	2.99612
Within	0.387935	12	0.032328			
Total	4.314896	23				

Harvest 2 Fresh *L. perenne* L. Samples: ANOVA with Two Factor with Replication

SUMMARY	0	1	2.5	5	10	Total
1						
Count	2	2	2	2	2	10
Sum	12.3042	13.5115	10.5721	2.3198	0.4619	39.1695
Average	6.1521	6.75575	5.28605	1.1599	0.23095	3.91695
Variance	1.282241	0.587636	0.628657	0.225523	0.003952	8.32912
2						
Count	2	2	2	2	2	10
Sum	14.5353	9.5639	13.1882	12.7217	1.2825	51.2916
Average	7.26765	4.78195	6.5941	6.36085	0.64125	5.12916
Variance	0.115056	0.029792	1.865153	0.702942	0.084913	6.643793
3						
Count	2	2	2	2	2	10
Sum	16.0114	14.5335	12.2618	1.9652	1.7085	46.4804
Average	8.0057	7.26675	6.1309	0.9826	0.85425	4.64804
Variance	0.00026	0.132561	1.485743	0.054186	0.110779	10.9001
Total						
Count	6	6	6	6	6	
Sum	42.8509	37.6089	36.0221	17.0067	3.4529	
Average	7.141817	6.26815	6.003683	2.83445	0.575483	
Variance	0.976178	1.527496	1.14782	7.664116	0.120225	

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Sample	7.451407	2	3.725704	7.645715	0.005138	3.68232
Columns	183.1294	4	45.78234	93.95238	1.97E-10	3.055568
Interaction	42.41837	8	5.302297	10.88112	5.3E-05	2.640797
Within	7.309396	15	0.487293			
Total	240.3085	29				

Harvest 2 Dry *L. perenne* L. Samples: ANOVA with Two Factor with Replication

SUMMARY	0	1	2.5	5	10	Total
1						
Count	2	2	2	2	2	10
Sum	3.1656	3.0974	2.4334	0.7282	0.2204	9.645
Average	1.5828	1.5487	1.2167	0.3641	0.1102	0.9645
Variance	0.000977	0.1152	0.000899	0.005101	7.94E-05	0.430806
2						
Count	2	2	2	2	2	10
Sum	3.9257	2.4114	3.1447	3.319	0.2568	13.0576
Average	1.96285	1.2057	1.57235	1.6595	0.1284	1.30576
Variance	0.001295	1.15E-05	0.118049	0.09928	0.00508	0.47467
3						
Count	2	2	2	2	2	10
Sum	3.9615	3.265	2.7612	0.4388	0.4323	10.8588
Average	1.98075	1.6325	1.3806	0.2194	0.21615	1.08588
Variance	0.002119	0.02933	0.080401	0.000737	0.018876	0.613199
Total						
Count	6	6	6	6	6	
Sum	11.0528	8.7738	8.3393	4.486	0.9095	
Average	1.842133	1.4623	1.389883	0.747667	0.151583	
Variance	0.041295	0.069819	0.065219	0.524075	0.007375	

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Sample	0.598462	2	0.299231	9.401205	0.002257	3.68232
Columns	10.72763	4	2.681906	84.25977	4.31E-10	3.055568
Interaction	2.463014	8	0.307877	9.67283	0.000107	2.640797
Within	0.477435	15	0.031829			
Total	14.26654	29				

Harvest 3 Fresh *A. stolonifera* L. Samples: ANOVA with Two Factor with Replication

SUMMARY	0	1	2.5	5	10	Total
1						
Count	2	2	2	2	2	10
Sum	3.1898	5.7314	3.8198	7.2437	0.6769	20.6616
Average	1.5949	2.8657	1.9099	3.62185	0.33845	2.06616
Variance	0.065667	0.128829	0.002506	1.160526	0.031727	1.552344
2						
Count	2	2	2	2	2	10
Sum	3.7835	5.9728	6.1229	5.039	0.3844	21.3026
Average	1.89175	2.9864	3.06145	2.5195	0.1922	2.13026
Variance	0.00509	0.611618	0.18042	0.000107	0.012044	1.326489
3						
Count	2	2	2	2	2	10
Sum	4.8042	5.83	6.9631	2.9261	1.348	21.8714
Average	2.4021	2.915	3.48155	1.46305	0.674	2.18714
Variance	0.004724	0.119658	0.073	0.00973	0.431892	1.196641
Total						
Count	6	6	6	6	6	
Sum	11.7775	17.5342	16.9058	15.2088	2.4093	
Average	1.962917	2.922367	2.817633	2.5348	0.40155	
Variance	0.148449	0.174967	0.58087	1.166297	0.143948	

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Sample	0.073268	2	0.036634	0.193656	0.825969	3.68232
Columns	25.67988	4	6.419971	33.93771	2.36E-07	3.055568
Interaction	8.161849	8	1.020231	5.393219	0.002524	2.640797
Within	2.837539	15	0.189169			
Total	36.75254	29				

Harvest 3 Dry *A. stolonifera* L. Samples: ANOVA with Two Factor with Replication

SUMMARY	0	1	2.5	5	10	Total
1						
Count	2	2	2	2	2	10
Sum	0.5889	1.1319	0.7328	1.4301	0.0556	3.9393
Average	0.29445	0.56595	0.3664	0.71505	0.0278	0.39393
Variance	0.004409	0.005714	2E-06	0.050086	9.68E-06	0.068339
2						
Count	2	2	2	2	2	10
Sum	0.797	1.1456	1.3064	0.9964	0.0558	4.3012
Average	0.3985	0.5728	0.6532	0.4982	0.0279	0.43012
Variance	0.000113	0.024686	0.003698	2.59E-05	0.000293	0.055988
3						
Count	2	2	2	2	2	10
Sum	1.162	1.2412	1.6105	0.5598	0.2466	4.8201
Average	0.581	0.6206	0.80525	0.2799	0.1233	0.48201
Variance	0.000233	0.01296	0.003019	0.002621	0.010746	0.070622
Total						
Count	6	6	6	6	6	
Sum	2.5479	3.5187	3.6497	2.9863	0.358	
Average	0.42465	0.58645	0.608283	0.497717	0.059667	
Variance	0.017783	0.009381	0.041072	0.048418	0.004639	

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Sample	0.039201	2	0.019601	2.478687	0.117465	3.68232
Columns	1.187275	4	0.296819	37.53559	1.2E-07	3.055568
Interaction	0.448652	8	0.056082	7.09205	0.000614	2.640797
Within	0.118615	15	0.007908			
Total	1.793744	29				

Harvest 3 Fresh *F. rubra* L. Samples: ANOVA with Two Factor with Replication

SUMMARY	0	1	2.5	5	10	Total
1						
Count	2	2	2	2	2	10
Sum	3.628	4.3787	4.9226	5.2358	0.4484	18.6135
Average	1.814	2.18935	2.4613	2.6179	0.2242	1.86135
Variance	0.000192	0.055745	0.24193	0.09636	0.000196	0.871023
2						
Count	2	2	2	2	2	10
Sum	4.5795	5.1436	5.891	5.0073	0.489	21.1104
Average	2.28975	2.5718	2.9455	2.50365	0.2445	2.11104
Variance	0.072466	0.018663	0.36125	0.579641	0.012928	1.133589
3						
Count	2	2	2	2	2	10
Sum	4.5169	4.7514	4.8947	2.1919	0.1589	16.5138
Average	2.25845	2.3757	2.44735	1.09595	0.07945	1.65138
Variance	1.291707	0.376886	0.02322	0.439078	0.000548	1.193762
Total						
Count	6	6	6	6	6	
Sum	12.7244	14.2737	15.7083	12.435	1.0963	
Average	2.120733	2.37895	2.61805	2.0725	0.182717	
Variance	0.32952	0.119519	0.189653	0.797817	0.009215	

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Sample	1.059066	2	0.529533	2.224424	0.142554	3.68232
Columns	22.61581	4	5.653953	23.75071	2.42E-06	3.055568
Interaction	2.598741	8	0.324843	1.364575	0.287313	2.640797
Within	3.57081	15	0.238054			
Total	29.84443	29				

Harvest 3 Dry *F. rubra* L. Samples: ANOVA with Two Factor with Replication

SUMMARY	0	1	2.5	5	10	Total
1						
Count	2	2	2	2	2	10
Sum	0.8965	1.1109	1.2745	1.332	0.04	4.6539
Average	0.44825	0.55545	0.63725	0.666	0.02	0.46539
Variance	8.32E-05	0.007626	0.017466	0.005366	0.0002	0.064873
2						
Count	2	2	2	2	2	10
Sum	1.0628	1.3375	1.3676	1.0976	0.0581	4.9236
Average	0.5314	0.66875	0.6838	0.5488	0.02905	0.49236
Variance	0.00312	0.005274	0.018355	0.035805	0.00024	0.070783
3						
Count	2	2	2	2	2	10
Sum	1.0382	1.1643	1.2804	0.4516	0.07	4.0045
Average	0.5191	0.58215	0.6402	0.2258	0.035	0.40045
Variance	0.068895	0.021945	0.001694	0.030406	5E-05	0.073361
Total						
Count	6	6	6	6	6	
Sum	2.9975	3.6127	3.9225	2.8812	0.1681	
Average	0.499583	0.602117	0.65375	0.4802	0.028017	
Variance	0.016031	0.009776	0.008046	0.055894	0.000144	

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Sample	0.04464	2	0.02232	1.546246	0.245158	3.68232
Columns	1.47634	4	0.369085	25.56876	1.51E-06	3.055568
Interaction	0.188289	8	0.023536	1.630492	0.197316	2.640797
Within	0.216525	15	0.014435			
Total	1.925794	29				

Harvest 3 Fresh *P. trivialis* L. Samples: ANOVA with Two Factor with Replication

SUMMARY	0	1	2.5	5	10	Total
1						
Count	2	2	2	2	2	10
Sum	3.2138	6.11	4.1878	4.8697	1.2936	19.6749
Average	1.6069	3.055	2.0939	2.43485	0.6468	1.96749
Variance	0.065885	1.356305	0.14775	0.189297	0.013415	0.928368
2						
Count	2	2	2	2	2	10
Sum	3.2028	4.7112	5.0122	4.7861	0.5957	18.308
Average	1.6014	2.3556	2.5061	2.39305	0.29785	1.8308
Variance	0.053203	0.336528	1.386779	0.008515	0.014913	0.966689
3						
Count	2	2	2	2	2	10
Sum	4.6967	5.2184	4.4334	2.7532	0.2572	17.3589
Average	2.34835	2.6092	2.2167	1.3766	0.1286	1.73589
Variance	6.84E-05	0.159161	0.017785	0.002812	0.033076	0.930639
Total						
Count	6	6	6	6	6	
Sum	11.1133	16.0396	13.6334	12.409	2.1465	
Average	1.852217	2.673267	2.272233	2.068167	0.35775	
Variance	0.171526	0.470693	0.346295	0.327433	0.06814	

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Sample	0.271102	2	0.135551	0.537121	0.595259	3.68232
Columns	18.78193	4	4.695482	18.60583	1.11E-05	3.055568
Interaction	2.863844	8	0.35798	1.418496	0.266272	2.640797
Within	3.785492	15	0.252366			
Total	25.70237	29				

Harvest 3 Dry *P. trivialis* L. Samples: ANOVA with Two Factor with Replication

SUMMARY	0	1	2.5	5	10	Total
1						
Count	2	2	2	2	2	10
Sum	0.7308	1.4559	1.0044	1.1884	0.2142	4.5937
Average	0.3654	0.72795	0.5022	0.5942	0.1071	0.45937
Variance	0.00616	0.072619	0.02016	0.003784	0.001352	0.06158
2						
Count	2	2	2	2	2	10
Sum	0.7558	1.0745	1.1896	1.1363	0.0554	4.2116
Average	0.3779	0.53725	0.5948	0.56815	0.0277	0.42116
Variance	0.002738	0.023523	0.081689	0.001966	0.000685	0.061604
3						
Count	2	2	2	2	2	10
Sum	1.1325	1.2127	1.0773	0.599	-0.0003	4.0212
Average	0.56625	0.60635	0.53865	0.2995	-0.00015	0.40212
Variance	0.001035	0.010068	0.004734	0.000242	4.5E-08	0.059485
Total						
Count	6	6	6	6	6	
Sum	2.6191	3.7431	3.2713	2.9237	0.2693	
Average	0.436517	0.62385	0.545217	0.487283	0.044883	
Variance	0.012116	0.028699	0.023057	0.022492	0.002885	

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Sample	0.017	2	0.0085	0.552545	0.58676	3.68232
Columns	1.214768	4	0.303692	19.74126	7.71E-06	3.055568
Interaction	0.198492	8	0.024812	1.612854	0.202294	2.640797
Within	0.230754	15	0.015384			
Total	1.661015	29				

Harvest 3 Fresh *L. perenne* L. Samples: ANOVA with Two Factor with Replication

SUMMARY	0	1	2.5	5	10	Total
1						
Count	2	2	2	2	2	10
Sum	5.0825	6.7838	9.7436	4.0706	1.249	26.9295
Average	2.54125	3.3919	4.8718	2.0353	0.6245	2.69295
Variance	0.076167	1.33694	0.025628	0.28607	0.198576	2.429247
2						
Count	2	2	2	2	2	10
Sum	5.0435	5.8442	6.2025	5.1706	1.9637	24.2245
Average	2.52175	2.9221	3.10125	2.5853	0.98185	2.42245
Variance	0.001378	0.002918	0.204736	0.228758	0.239086	0.702348
3						
Count	2	2	2	2	2	10
Sum	6.4371	8.0165	7.3383	2.7223	1.7652	26.2794
Average	3.21855	4.00825	3.66915	1.36115	0.8826	2.62794
Variance	0.020301	0.01519	0.017804	0.047094	0.076128	1.794983
Total						
Count	6	6	6	6	6	
Sum	16.5631	20.6445	23.2844	11.9635	4.9779	
Average	2.760517	3.44075	3.880733	1.993917	0.82965	
Variance	0.145522	0.508386	0.703464	0.413121	0.12998	

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Sample	0.398742	2	0.199371	1.076993	0.36555	3.68232
Columns	35.23558	4	8.808895	47.5852	2.39E-08	3.055568
Interaction	6.326843	8	0.790855	4.27216	0.007528	2.640797
Within	2.776776	15	0.185118			
Total	44.73794	29				

Harvest 3 Dry *L. perenne* L. Samples: ANOVA with Two Factor with Replication

SUMMARY	0	1	2.5	5	10	Total
1						
Count	2	2	2	2	2	10
Sum	1.0556	1.4072	1.9057	0.8007	0.1991	5.3683
Average	0.5278	0.7036	0.95285	0.40035	0.09955	0.53683
Variance	0.002126	0.063867	0.00456	0.015051	0.010937	0.102017
2						
Count	2	2	2	2	2	10
Sum	1.1764	1.3927	1.4123	1.1524	0.3545	5.4883
Average	0.5882	0.69635	0.70615	0.5762	0.17725	0.54883
Variance	0.000432	0.000429	0.013662	0.02668	0.016362	0.047926
3						
Count	2	2	2	2	2	10
Sum	1.3982	1.7941	1.5425	0.5425	0.3127	5.59
Average	0.6991	0.89705	0.77125	0.27125	0.15635	0.559
Variance	0.001741	0.000515	1.86E-05	0.002319	0.00565	0.095334
Total						
Count	6	6	6	6	6	
Sum	3.6302	4.594	4.8605	2.4956	0.8663	
Average	0.605033	0.765667	0.810083	0.415933	0.144383	
Variance	0.006898	0.02333	0.016725	0.027555	0.007883	

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Sample	0.002463	2	0.001232	0.112403	0.89443	3.68232
Columns	1.798002	4	0.449501	41.02513	6.58E-08	3.055568
Interaction	0.245143	8	0.030643	2.79672	0.040989	2.640797
Within	0.164351	15	0.010957			
Total	2.209959	29				

Harvest 4 Fresh *A. stolonifera* L. Samples: ANOVA with Two Factor with Replication

SUMMARY	0	1	2.5	5	10	Total
1						
Count	2	2	2	2	2	10
Sum	2.49	3	2.36	3.82	1.03	12.7
Average	1.245	1.5	1.18	1.91	0.515	1.27
Variance	0.01445	0	0.08	0.08	0.21125	0.274244
2						
Count	2	2	2	2	2	10
Sum	2.16	2.56	3.07	2.79	0.6	11.18
Average	1.08	1.28	1.535	1.395	0.3	1.118
Variance	0.0128	0.0002	0.08405	0.00605	0.0722	0.230018
3						
Count	2	2	2	2	2	10
Sum	1.86	3.33	2.49	3.4	1.31	12.39
Average	0.93	1.665	1.245	1.7	0.655	1.239
Variance	0.0002	0.03645	0.13005	0.005	0.41405	0.249654
Total						
Count	6	6	6	6	6	
Sum	6.51	8.89	7.92	10.01	2.94	
Average	1.085	1.481667	1.32	1.668333	0.49	
Variance	0.02535	0.037177	0.0874	0.071857	0.16508	

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Sample	0.12902	2	0.06451	0.843819	0.449493	3.68232
Columns	4.979953	4	1.244988	16.285	2.47E-05	3.055568
Interaction	0.658547	8	0.082318	1.07676	0.428272	2.640797
Within	1.14675	15	0.07645			
Total	6.91427	29				

Harvest 4 Dry *A. stolonifera* L. Samples: ANOVA with Two Factor with Replication

SUMMARY	0	1	2.5	5	10	Total
1						
Count	2	2	2	2	2	10
Sum	0.62	0.75	0.61	0.88	0.2	3.06
Average	0.31	0.375	0.305	0.44	0.1	0.306
Variance	0	0.00045	0.00605	0.0098	0.0128	0.017716
2						
Count	2	2	2	2	2	10
Sum	0.6	0.72	0.84	0.69	0.14	2.99
Average	0.3	0.36	0.42	0.345	0.07	0.299
Variance	0.0008	0.0072	0.005	0.00245	0.0072	0.018721
3						
Count	2	2	2	2	2	10
Sum	0.57	0.87	0.8	0.81	0.35	3.4
Average	0.285	0.435	0.4	0.405	0.175	0.34
Variance	5E-05	0.00045	0.0162	0.00045	0.03645	0.016422
Total						
Count	6	6	6	6	6	
Sum	1.79	2.34	2.25	2.38	0.69	
Average	0.298333	0.39	0.375	0.396667	0.115	
Variance	0.000297	0.00288	0.00847	0.004387	0.01363	

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Sample	0.00962	2	0.00481	0.68486	0.519248	3.68232
Columns	0.337033	4	0.084258	11.99692	0.000142	3.055568
Interaction	0.033347	8	0.004168	0.593498	0.768991	2.640797
Within	0.10535	15	0.007023			
Total	0.48535	29				

Harvest 4 Fresh *F. rubra* L. Samples: ANOVA with Two Factor with Replication

SUMMARY	0	1	2.5	5	10	Total
1						
Count	2	2	2	2	2	10
Sum	2.54	2.39	2.65	2.99	0.35	10.92
Average	1.27	1.195	1.325	1.495	0.175	1.092
Variance	0.0072	0.00405	0.03645	0.13005	0.00045	0.264218
2						
Count	2	2	2	2	2	10
Sum	2.35	3.39	4.38	3.77	0.62	14.51
Average	1.175	1.695	2.19	1.885	0.31	1.451
Variance	0.03645	0.00605	0.2738	0.16245	0.0882	0.545677
3						
Count	2	2	2	2	2	10
Sum	2.35	3.22	2.46	1.68	0.25	9.96
Average	1.175	1.61	1.23	0.84	0.125	0.996
Variance	0.22445	0.245	0.0032	0.02	0.00845	0.332738
Total						
Count	6	6	6	6	6	
Sum	7.24	9	9.49	8.44	1.22	
Average	1.206667	1.5	1.581667	1.406667	0.203333	
Variance	0.056027	0.10828	0.286537	0.285587	0.026747	

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Sample	1.150407	2	0.575203	6.92321	0.007413	3.68232
Columns	7.618213	4	1.904553	22.92341	3.03E-06	3.055568
Interaction	1.419227	8	0.177403	2.135246	0.097745	2.640797
Within	1.24625	15	0.083083			
Total	11.4341	29				

Harvest 4 Dry *F. rubra* L. Samples: ANOVA with Two Factor with Replication

SUMMARY	0	1	2.5	5	10	Total
1						
Count	2	2	2	2	2	10
Sum	0.71	0.67	0.78	0.84	0.07	3.07
Average	0.355	0.335	0.39	0.42	0.035	0.307
Variance	0.00125	0.00125	0.0032	0.02	5E-05	0.024357
2						
Count	2	2	2	2	2	10
Sum	0.56	0.83	1.06	0.9	0.15	3.5
Average	0.28	0.415	0.53	0.45	0.075	0.35
Variance	0.0018	0.00045	0.0162	0.0098	0.00845	0.032333
3						
Count	2	2	2	2	2	10
Sum	0.6	0.78	0.62	0.41	0.07	2.48
Average	0.3	0.39	0.31	0.205	0.035	0.248
Variance	0.0162	0.0128	0.0002	0.00125	0.00125	0.019951
Total						
Count	6	6	6	6	6	
Sum	1.87	2.28	2.46	2.15	0.29	
Average	0.311667	0.38	0.41	0.358333	0.048333	
Variance	0.005057	0.00424	0.01384	0.020497	0.002377	

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Sample	0.052447	2	0.026223	4.177908	0.036118	3.68232
Columns	0.512167	4	0.128042	20.39963	6.29E-06	3.055568
Interaction	0.083453	8	0.010432	1.661976	0.188739	2.640797
Within	0.09415	15	0.006277			
Total	0.742217	29				

Harvest 4 Fresh *P. trivialis* L. Samples: ANOVA with Two Factor with Replication

SUMMARY	0	1	2.5	5	10	Total
1						
Count	2	2	2	2	2	10
Sum	2.18	3.41	2.1	2.11	1.73	11.53
Average	1.09	1.705	1.05	1.055	0.865	1.153
Variance	0.0648	0.18605	0	0.51005	0.02645	0.179001
2						
Count	2	2	2	2	2	10
Sum	1.66	4	2.98	2.51	0.52	11.67
Average	0.83	2	1.49	1.255	0.26	1.167
Variance	0	0.1682	0.2592	0.00045	0.005	0.435246
3						
Count	2	2	2	2	2	10
Sum	1.98	2.57	3.61	2.9	0.16	11.22
Average	0.99	1.285	1.805	1.45	0.08	1.122
Variance	0.0008	0.03645	0.49005	0.02	0.0128	0.440862
Total						
Count	6	6	6	6	6	
Sum	5.82	9.98	8.69	7.52	2.41	
Average	0.97	1.663333	1.448333	1.253333	0.401667	
Variance	0.02688	0.181427	0.264897	0.137307	0.144137	

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Sample	0.010607	2	0.005303	0.044683	0.956427	3.68232
Columns	5.733353	4	1.433338	12.07666	0.000137	3.055568
Interaction	1.982327	8	0.247791	2.087773	0.104295	2.640797
Within	1.7803	15	0.118687			
Total	9.506587	29				

Harvest 4 Dry *P. trivialis* L. Samples: ANOVA with Two Factor with Replication

SUMMARY	0	1	2.5	5	10	Total
1						
Count	2	2	2	2	2	10
Sum	0.64	1.01	0.63	0.8	0.44	3.52
Average	0.32	0.505	0.315	0.4	0.22	0.352
Variance	0.0098	0.00245	5E-05	0.0032	0.0032	0.012196
2						
Count	2	2	2	2	2	10
Sum	0.47	1.04	0.77	0.69	0.12	3.09
Average	0.235	0.52	0.385	0.345	0.06	0.309
Variance	5E-05	0.0072	0.01445	5E-05	0.0008	0.028966
3						
Count	2	2	2	2	2	10
Sum	0.56	0.73	1	0.77	0.05	3.11
Average	0.28	0.365	0.5	0.385	0.025	0.311
Variance	0.0002	0.01125	0.0242	0.00125	0.00125	0.032432
Total						
Count	6	6	6	6	6	
Sum	1.67	2.78	2.4	2.26	0.61	
Average	0.278333	0.463333	0.4	0.376667	0.101667	
Variance	0.003457	0.010027	0.01472	0.001547	0.009697	

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Sample	0.01178	2	0.00589	1.11272	0.354329	3.68232
Columns	0.476887	4	0.119222	22.52298	3.39E-06	3.055568
Interaction	0.106053	8	0.013257	2.504408	0.059681	2.640797
Within	0.0794	15	0.005293			
Total	0.67412	29				

Harvest 4 Fresh *L. perenne* L. Samples: ANOVA with Two Factor with Replication

SUMMARY	0	1	2.5	5	10	Total
1						
Count	2	2	2	2	2	10
Sum	2.12	4.1	5.52	3.29	0.58	15.61
Average	1.06	2.05	2.76	1.645	0.29	1.561
Variance	0.0648	0.605	0.0392	0.36125	0.045	0.912854
2						
Count	2	2	2	2	2	10
Sum	2.79	3.94	3.21	2.92	1.77	14.63
Average	1.395	1.97	1.605	1.46	0.885	1.463
Variance	0.00045	0.0392	0.00125	0.0098	0.04805	0.147846
3						
Count	2	2	2	2	2	10
Sum	3.51	3.52	4.62	3.17	1.27	16.09
Average	1.755	1.76	2.31	1.585	0.635	1.609
Variance	0.10125	0.2592	0.0128	0.18605	0.06845	0.399699
Total						
Count	6	6	6	6	6	
Sum	8.42	11.56	13.35	9.38	3.62	
Average	1.403333	1.926667	2.225	1.563333	0.603333	
Variance	0.129947	0.198627	0.28179	0.118547	0.103707	

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Sample	0.110747	2	0.055373	0.450984	0.645361	3.68232
Columns	9.091253	4	2.272813	18.51076	1.14E-05	3.055568
Interaction	2.210587	8	0.276323	2.250495	0.083612	2.640797
Within	1.84175	15	0.122783			
Total	13.25434	29				

Harvest 4 Dry *L. perenne* L. Samples: ANOVA with Two Factor with Replication

SUMMARY	0	1	2.5	5	10	Total
1						
Count	2	2	2	2	2	10
Sum	0.57	0.97	1.27	0.78	0.11	3.7
Average	0.285	0.485	0.635	0.39	0.055	0.37
Variance	0.00405	0.03645	0.00845	0.0162	0.00405	0.049978
2						
Count	2	2	2	2	2	10
Sum	0.77	0.96	0.8	0.75	0.42	3.7
Average	0.385	0.48	0.4	0.375	0.21	0.37
Variance	5E-05	0.0018	0.0002	0.00405	0.0032	0.009667
3						
Count	2	2	2	2	2	10
Sum	0.81	0.83	1.03	0.67	0.27	3.61
Average	0.405	0.415	0.515	0.335	0.135	0.361
Variance	0.00405	0.01445	0.00245	5E-05	0.00405	0.020632
Total						
Count	6	6	6	6	6	
Sum	2.15	2.76	3.1	2.2	0.8	
Average	0.358333	0.46	0.516667	0.366667	0.133333	
Variance	0.004937	0.01176	0.013267	0.004707	0.007067	

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Sample	0.00054	2	0.00027	0.039112	0.961741	3.68232
Columns	0.514347	4	0.128587	18.62675	1.1E-05	3.055568
Interaction	0.104593	8	0.013074	1.893892	0.136326	2.640797
Within	0.10355	15	0.006903			
Total	0.72303	29				

Harvest 5 Fresh *A. stolonifera* L. Samples: ANOVA with Two Factor with Replication

SUMMARY	0	1	2.5	5	10	Total
1						
Count	2	2	2	2	2	10
Sum	1.09	1.62	1.35	3.21	2.37	9.64
Average	0.545	0.81	0.675	1.605	1.185	0.964
Variance	5E-05	0.0098	0.01445	0.08405	0.55125	0.238293
2						
Count	2	2	2	2	2	10
Sum	1.83	2.21	2.05	2.23	2.67	10.99
Average	0.915	1.105	1.025	1.115	1.335	1.099
Variance	0.01125	0.07605	0.00605	0.00605	0.36125	0.072366
3						
Count	2	2	2	2	2	10
Sum	1.3	2.49	1.25	4.03	1.48	10.55
Average	0.65	1.245	0.625	2.015	0.74	1.055
Variance	0.0008	0.18605	5E-05	0.01805	0.3872	0.378206
Total						
Count	6	6	6	6	6	
Sum	4.22	6.32	4.65	9.47	6.52	
Average	0.703333	1.053333	0.775	1.578333	1.086667	
Variance	0.031507	0.093827	0.04211	0.184057	0.336547	

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Sample	0.094807	2	0.047403	0.415236	0.667545	3.68232
Columns	2.854353	4	0.713588	6.250774	0.00363	3.055568
Interaction	1.633027	8	0.204128	1.78809	0.158052	2.640797
Within	1.7124	15	0.11416			
Total	6.294587	29				

Harvest 5 Dry *A. stolonifera* L. Samples: ANOVA with Two Factor with Replication

SUMMARY	0	1	2.5	5	10	Total
1						
Count	2	2	2	2	2	10
Sum	0.3	0.51	0.36	0.75	0.57	2.49
Average	0.15	0.255	0.18	0.375	0.285	0.249
Variance	0.0008	0.00125	0.0032	0.00405	0.04205	0.012766
2						
Count	2	2	2	2	2	10
Sum	0.42	0.57	0.42	0.57	0.56	2.54
Average	0.21	0.285	0.21	0.285	0.28	0.254
Variance	0.0008	0.01125	0.0008	0.00125	0.0242	0.005693
3						
Count	2	2	2	2	2	10
Sum	0.34	0.57	0.34	1.02	0.37	2.64
Average	0.17	0.285	0.17	0.51	0.185	0.264
Variance	0	0.01125	0	0.005	0.04205	0.025338
Total						
Count	6	6	6	6	6	
Sum	1.06	1.65	1.12	2.34	1.5	
Average	0.176667	0.275	0.186667	0.39	0.25	
Variance	0.001067	0.00499	0.001147	0.01232	0.0242	

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Sample	0.001167	2	0.000583	0.059142	0.942792	3.68232
Columns	0.17672	4	0.04418	4.479216	0.013999	3.055568
Interaction	0.0695	8	0.008687	0.880787	0.553907	2.640797
Within	0.14795	15	0.009863			
Total	0.395337	29				

Harvest 5 Fresh *F. rubra* L. Samples: ANOVA with Two Factor with Replication

SUMMARY	0	1	2.5	5	10	Total
1						
Count	2	2	2	2	2	10
Sum	2.9	2.45	2.44	2.17	0.86	10.82
Average	1.45	1.225	1.22	1.085	0.43	1.082
Variance	0.3042	0.00045	0.2178	0.02645	0.0242	0.197018
2						
Count	2	2	2	2	2	10
Sum	1.26	1.93	2.83	3.06	0.96	10.04
Average	0.63	0.965	1.415	1.53	0.48	1.004
Variance	0.005	0.00045	0.31205	0.0098	0.2178	0.252027
3						
Count	2	2	2	2	2	10
Sum	2.16	2.27	1.63	1.76	0.67	8.49
Average	1.08	1.135	0.815	0.88	0.335	0.849
Variance	0.0648	0.16245	0.00605	0.0018	0.01445	0.116943
Total						
Count	6	6	6	6	6	
Sum	6.32	6.65	6.9	6.99	2.49	
Average	1.053333	1.108333	1.15	1.165	0.415	
Variance	0.209707	0.046617	0.18212	0.09595	0.05563	

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Sample	0.281327	2	0.140663	1.542643	0.245892	3.68232
Columns	2.4251	4	0.606275	6.648967	0.00276	3.055568
Interaction	1.30104	8	0.16263	1.78355	0.159061	2.640797
Within	1.36775	15	0.091183			
Total	5.375217	29				

Harvest 5 Dry *F. rubra* L. Samples: ANOVA with Two Factor with Replication

SUMMARY	0	1	2.5	5	10	Total
1						
Count	2	2	2	2	2	10
Sum	0.71	0.57	0.61	0.5	0.12	2.51
Average	0.355	0.285	0.305	0.25	0.06	0.251
Variance	0.03125	5E-05	0.03125	0.0032	0.0018	0.018921
2						
Count	2	2	2	2	2	10
Sum	0.23	0.48	0.63	0.7	0.21	2.25
Average	0.115	0.24	0.315	0.35	0.105	0.225
Variance	0.00045	0	0.01445	0.0018	0.01805	0.015072
3						
Count	2	2	2	2	2	10
Sum	0.49	0.51	0.36	0.39	0.11	1.86
Average	0.245	0.255	0.18	0.195	0.055	0.186
Variance	0.00245	0.01125	0.0002	5E-05	0.00045	0.007271
Total						
Count	6	6	6	6	6	
Sum	1.43	1.56	1.6	1.59	0.44	
Average	0.238333	0.26	0.266667	0.265	0.073333	
Variance	0.018377	0.00268	0.013707	0.00595	0.004667	

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Sample	0.021407	2	0.010703	1.37575	0.282762	3.68232
Columns	0.165887	4	0.041472	5.330548	0.007112	3.055568
Interaction	0.088793	8	0.011099	1.426628	0.263232	2.640797
Within	0.1167	15	0.00778			
Total	0.392787	29				

Harvest 5 Fresh *P. trivialis* L. Samples: ANOVA with Two Factor with Replication

SUMMARY	0	1	2.5	5	10	Total
1						
Count	2	2	2	2	2	10
Sum	1.3	2.55	0.97	2.35	2.62	9.79
Average	0.65	1.275	0.485	1.175	1.31	0.979
Variance	0.0392	0.45125	0.01125	0.02645	0.08	0.19821
2						
Count	2	2	2	2	2	10
Sum	1.4	2.66	2.41	1.97	1.2	9.64
Average	0.7	1.33	1.205	0.985	0.6	0.964
Variance	0.0288	0.125	0.15125	0.00405	0.18	0.142049
3						
Count	2	2	2	2	2	10
Sum	1.85	2.3	2.84	2.79	0.2	9.98
Average	0.925	1.15	1.42	1.395	0.1	0.998
Variance	0.06845	0.045	0.0648	0.04205	0.02	0.286818
Total						
Count	6	6	6	6	6	
Sum	4.55	7.51	6.22	7.11	4.02	
Average	0.758333	1.251667	1.036667	1.185	0.67	
Variance	0.044457	0.131057	0.237307	0.04819	0.35176	

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Sample	0.005807	2	0.002903	0.03256	0.968033	3.68232
Columns	1.585647	4	0.396412	4.445572	0.014396	3.055568
Interaction	2.720493	8	0.340062	3.813633	0.012317	2.640797
Within	1.33755	15	0.08917			
Total	5.649497	29				

Harvest 5 Dry *P. trivialis* L. Samples: ANOVA with Two Factor with Replication

SUMMARY	0	1	2.5	5	10	Total
1						
Count	2	2	2	2	2	10
Sum	0.31	0.62	0.23	0.65	0.64	2.45
Average	0.155	0.31	0.115	0.325	0.32	0.245
Variance	0.00245	0.0338	0.00405	5E-05	0.0072	0.01445
2						
Count	2	2	2	2	2	10
Sum	0.37	0.67	0.62	0.49	0.25	2.4
Average	0.185	0.335	0.31	0.245	0.125	0.24
Variance	0.00245	0.01125	0.0098	5E-05	0.01445	0.010933
3						
Count	2	2	2	2	2	10
Sum	0.47	0.59	0.69	0.67	0.01	2.43
Average	0.235	0.295	0.345	0.335	0.005	0.243
Variance	0.00045	0.00605	0.00245	0.00245	5E-05	0.018668
Total						
Count	6	6	6	6	6	
Sum	1.15	1.88	1.54	1.81	0.9	
Average	0.191667	0.313333	0.256667	0.301667	0.15	
Variance	0.002377	0.010547	0.015547	0.002457	0.02456	

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Sample	0.000127	2	6.33E-05	0.009794	0.99026	3.68232
Columns	0.119153	4	0.029788	4.606443	0.012605	3.055568
Interaction	0.180307	8	0.022538	3.485309	0.017848	2.640797
Within	0.097	15	0.006467			
Total	0.396587	29				

Harvest 5 Fresh *L. perenne* L. Samples: ANOVA with Two Factor with Replication

SUMMARY	0	1	2.5	5	10	20	Total
1							
Count	2	2	2	2	2	2	12
Sum	1.53	3.21	3.38	2.32	1.01	0	11.45
Average	0.765	1.605	1.69	1.16	0.505	0	0.954167
Variance	0.01805	0.78125	0	0.1352	0.15125	0	0.49059
2							
Count	2	2	2	2	2	2	12
Sum	2.35	3.23	1.94	2.49	2.38	0.3	12.69
Average	1.175	1.615	0.97	1.245	1.19	0.15	1.0575
Variance	0.08405	0.00605	0.0648	0.19845	0.0648	0.0008	0.25782
3							
Count	2	2	2	2	2	2	12
Sum	2.37	2.5	3.29	3.35	1.86	0.21	13.58
Average	1.185	1.25	1.645	1.675	0.93	0.105	1.131667
Variance	0.19845	0.125	0.00405	0.12005	0.0648	0.00045	0.350306
Total							
Count	6	6	6	6	6	6	
Sum	6.25	8.94	8.61	8.16	5.25	0.51	
Average	1.041667	1.49	1.435	1.36	0.875	0.085	
Variance	0.106057	0.21704	0.14391	0.15172	0.15183	0.00499	

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Sample	0.190739	2	0.095369	0.85088	0.443514	3.554557
Columns	8.398889	5	1.679778	14.98686	7.1E-06	2.772853
Interaction	1.669494	10	0.166949	1.489512	0.221797	2.411702
Within	2.0175	18	0.112083			
Total	12.27662	35				

Harvest 5 Dry *L. perenne* L. Samples: ANOVA with Two Factor with Replication

SUMMARY	0	1	2.5	5	10	20	Total
1							
Count	2	2	2	2	2	2	12
Sum	0.42	0.75	0.78	0.57	0.24	0	2.76
Average	0.21	0.375	0.39	0.285	0.12	0	0.23
Variance	0	0.04805	0.0018	0.00845	0.02	0	0.028036
2							
Count	2	2	2	2	2	2	12
Sum	0.56	0.74	0.41	0.58	0.57	0.03	2.89
Average	0.28	0.37	0.205	0.29	0.285	0.015	0.240833
Variance	0.005	0	0.00605	0.0128	0.00845	5E-05	0.016554
3							
Count	2	2	2	2	2	2	12
Sum	0.53	0.57	0.75	0.74	0.38	0.03	3
Average	0.265	0.285	0.375	0.37	0.19	0.015	0.25
Variance	0.01445	0.00605	5E-05	0.0072	0.0032	5E-05	0.019236
Total							
Count	6	6	6	6	6	6	
Sum	1.51	2.06	1.94	1.89	1.19	0.06	
Average	0.251667	0.343333	0.323333	0.315	0.198333	0.01	
Variance	0.004977	0.012867	0.010027	0.00751	0.011817	0.00008	

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Sample	0.002406	2	0.001203	0.152842	0.859368	3.554557
Columns	0.468114	5	0.093623	11.897	3.42E-05	2.772853
Interaction	0.092328	10	0.009233	1.173244	0.368113	2.411702
Within	0.14165	18	0.007869			
Total	0.704497	35				

Harvest 6 Fresh *A. stolonifera* L. Samples: ANOVA with Two Factor with Replication

SUMMARY	0	1	2.5	5	10	Total
1						
Count	2	2	2	2	2	10
Sum	1.83	2.34	1.89	2.49	2.71	11.26
Average	0.915	1.17	0.945	1.245	1.355	1.126
Variance	0.00845	0.005	0.00845	0.02645	0.04805	0.043116
2						
Count	2	2	2	2	2	10
Sum	1.96	2.61	2.14	2.56	3.44	12.71
Average	0.98	1.305	1.07	1.28	1.72	1.271
Variance	0.0008	0.04205	0.005	0.0242	0.0018	0.081077
3						
Count	2	2	2	2	2	10
Sum	1.62	2.7	1.74	3.04	2.28	11.38
Average	0.81	1.35	0.87	1.52	1.14	1.138
Variance	0.0032	0.0032	0.0242	0.0338	0.005	0.089996
Total						
Count	6	6	6	6	6	
Sum	5.41	7.65	5.77	8.09	8.43	
Average	0.901667	1.275	0.961667	1.348333	1.405	
Variance	0.008377	0.01707	0.015697	0.034817	0.07975	

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Sample	0.129527	2	0.064763	4.05362	0.039136	3.68232
Columns	1.278667	4	0.319667	20.00835	7.09E-06	3.055568
Interaction	0.409373	8	0.051172	3.2029	0.024876	2.640797
Within	0.23965	15	0.015977			
Total	2.057217	29				

Harvest 6 Dry *A. stolonifera* L. Samples: ANOVA with Two Factor with Replication

SUMMARY	0	1	2.5	5	10	Total
1						
Count	2	2	2	2	2	10
Sum	0.22	0.39	0.29	0.42	0.45	1.77
Average	0.11	0.195	0.145	0.21	0.225	0.177
Variance	0.0008	0.00045	5E-05	0.0018	0.00125	0.002534
2						
Count	2	2	2	2	2	10
Sum	0.19	0.42	0.37	0.45	0.64	2.07
Average	0.095	0.21	0.185	0.225	0.32	0.207
Variance	5E-05	0.0018	0.00125	5E-05	0.0002	0.006179
3						
Count	2	2	2	2	2	10
Sum	0.13	0.41	0.22	0.48	0.32	1.56
Average	0.065	0.205	0.11	0.24	0.16	0.156
Variance	5E-05	5E-05	0.0018	0.0008	0.0032	0.005071
Total						
Count	6	6	6	6	6	
Sum	0.54	1.22	0.88	1.35	1.41	
Average	0.09	0.203333	0.146667	0.225	0.235	
Variance	0.0006	0.000507	0.001747	0.00071	0.00611	

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Sample	0.01314	2	0.00657	7.246324	0.006278	3.68232
Columns	0.088833	4	0.022208	24.49449	1.99E-06	3.055568
Interaction	0.021627	8	0.002703	2.981618	0.032548	2.640797
Within	0.0136	15	0.000907			
Total	0.1372	29				

Harvest 6 Fresh *F. rubra* L. Samples: ANOVA with Two Factor with Replication

SUMMARY	0	1	2.5	5	10	Total
1						
Count	2	2	2	2	2	10
Sum	3.11	3.34	3.51	2.45	1.56	13.97
Average	1.555	1.67	1.755	1.225	0.78	1.397
Variance	0.10125	0.0098	0.06845	5E-05	0.1568	0.179134
2						
Count	2	2	2	2	2	10
Sum	1.58	1.9	2.5	3.69	1.38	11.05
Average	0.79	0.95	1.25	1.845	0.69	1.105
Variance	0.0098	0.0288	0.1682	0.10125	0.3042	0.26005
3						
Count	2	2	2	2	2	10
Sum	3.35	0	1.6	2.22	0.82	7.99
Average	1.675	0	0.8	1.11	0.41	0.799
Variance	0.51005	0	0.0018	0.0128	0.0032	0.426166
Total						
Count	6	6	6	6	6	
Sum	8.04	5.24	7.61	8.36	3.76	
Average	1.34	0.873333	1.268333	1.393333	0.626667	
Variance	0.3086	0.569027	0.230297	0.147867	0.122627	

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Sample	1.788347	2	0.894173	9.084358	0.002601	3.68232
Columns	2.684413	4	0.671103	6.818077	0.002464	3.055568
Interaction	3.627287	8	0.453411	4.606429	0.00535	2.640797
Within	1.47645	15	0.09843			
Total	9.576497	29				

Harvest 6 Dry *F. rubra* L. Samples: ANOVA with Two Factor with Replication

SUMMARY	0	1	2.5	5	10	Total
1						
Count	2	2	2	2	2	10
Sum	0.48	0.5	0.57	0.27	0.17	1.99
Average	0.24	0.25	0.285	0.135	0.085	0.199
Variance	0.0032	0.0002	0.00605	5E-05	0.00605	0.008121
2						
Count	2	2	2	2	2	10
Sum	0.16	0.21	0.37	0.6	0.22	1.56
Average	0.08	0.105	0.185	0.3	0.11	0.156
Variance	0.0008	0.00125	0.00605	0.0072	0	0.008827
3						
Count	2	2	2	2	2	10
Sum	0.52	0	0.12	0.27	0.07	0.98
Average	0.26	0	0.06	0.135	0.035	0.098
Variance	0.0242	0	0	5E-05	5E-05	0.012173
Total						
Count	6	6	6	6	6	
Sum	1.16	0.71	1.06	1.14	0.46	
Average	0.193333	0.118333	0.176667	0.19	0.076667	
Variance	0.013427	0.012897	0.012587	0.00872	0.002387	

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Sample	0.05138	2	0.02569	6.987307	0.007171	3.68232
Columns	0.063387	4	0.015847	4.310063	0.016128	3.055568
Interaction	0.143553	8	0.017944	4.880553	0.004085	2.640797
Within	0.05515	15	0.003677			
Total	0.31347	29				

Harvest 6 Fresh *P. trivialis* L. Samples: ANOVA with Two Factor with Replication

SUMMARY	0	1	2.5	5	10	Total
1						
Count	2	2	2	2	2	10
Sum	1.42	2.78	1.34	3.17	2.22	10.93
Average	0.71	1.39	0.67	1.585	1.11	1.093
Variance	0.02	0.2738	0.0512	0.21125	0.0882	0.217423
2						
Count	2	2	2	2	2	10
Sum	1.48	2.79	2	2.1	1.55	9.92
Average	0.74	1.395	1	1.05	0.775	0.992
Variance	0.0648	0.00605	0.1568	0.0008	0.03645	0.090862
3						
Count	2	2	2	2	2	10
Sum	2.56	2.32	1.85	3	0.66	10.39
Average	1.28	1.16	0.925	1.5	0.33	1.039
Variance	0.0098	0.0338	0.02645	0.005	0	0.186321
Total						
Count	6	6	6	6	6	
Sum	5.46	7.89	5.19	8.27	4.43	
Average	0.91	1.315	0.865	1.378333	0.738333	
Variance	0.10124	0.07715	0.07083	0.109537	0.147417	

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Sample	0.051087	2	0.025543	0.389222	0.684232	3.68232
Columns	1.97168	4	0.49292	7.510971	0.001573	3.055568
Interaction	1.49538	8	0.186923	2.848271	0.038416	2.640797
Within	0.9844	15	0.065627			
Total	4.502547	29				

Harvest 6 Dry *P. trivialis* L. Samples: ANOVA with Two Factor with Replication

SUMMARY	0	1	2.5	5	10	Total
1						
Count	2	2	2	2	2	10
Sum	0.06	0.44	0.13	0.52	0.34	1.49
Average	0.03	0.22	0.065	0.26	0.17	0.149
Variance	0.0002	0.0162	0.00405	0.0072	0.0072	0.012543
2						
Count	2	2	2	2	2	10
Sum	0.17	0.57	0.29	0.3	0.17	1.5
Average	0.085	0.285	0.145	0.15	0.085	0.15
Variance	0.00405	5E-05	0.00845	0.0008	0.00605	0.008089
3						
Count	2	2	2	2	2	10
Sum	0.4	0.31	0.17	0.44	0.28	1.6
Average	0.2	0.155	0.085	0.22	0.14	0.16
Variance	0.0032	0.00605	0.00605	0.0002	0.0032	0.004578
Total						
Count	6	6	6	6	6	
Sum	0.63	1.32	0.59	1.26	0.79	
Average	0.105	0.22	0.098333	0.21	0.131667	
Variance	0.00751	0.00784	0.005097	0.00412	0.004777	

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Sample	0.00074	2	0.00037	0.07608	0.927098	3.68232
Columns	0.080913	4	0.020228	4.159356	0.018334	3.055568
Interaction	0.073027	8	0.009128	1.876971	0.139579	2.640797
Within	0.07295	15	0.004863			
Total	0.22763	29				

Harvest 6 Fresh *L. perenne* L. Samples: ANOVA with Two Factor with Replication

SUMMARY	0	1	2.5	5	10	Total
1						
Count	2	2	2	2	2	10
Sum	1.4	2.47	2.54	2.39	0.91	9.71
Average	0.7	1.235	1.27	1.195	0.455	0.971
Variance	0.0072	0.78125	0.0032	0.21125	0.04205	0.238099
2						
Count	2	2	2	2	2	10
Sum	2.48	2.97	2.02	4.02	2.55	14.04
Average	1.24	1.485	1.01	2.01	1.275	1.404
Variance	0.0968	0.18605	0.0578	0.9248	0.00045	0.267893
3						
Count	2	2	2	2	2	10
Sum	2.3	1.97	2.73	2.84	2.19	12.03
Average	1.15	0.985	1.365	1.42	1.095	1.203
Variance	0.18	0.06845	0.04205	0.0392	0.00245	0.066979
Total						
Count	6	6	6	6	6	
Sum	6.18	7.41	7.29	9.25	5.65	
Average	1.03	1.235	1.215	1.541667	0.941667	
Variance	0.12376	0.25715	0.04763	0.376777	0.157577	

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Sample	0.939047	2	0.469523	2.664718	0.102269	3.68232
Columns	1.28132	4	0.32033	1.817991	0.177895	3.055568
Interaction	1.23242	8	0.154053	0.874305	0.55845	2.640797
Within	2.643	15	0.1762			
Total	6.095787	29				

Harvest 6 Dry *L. perenne* L. Samples: ANOVA with Two Factor with Replication

SUMMARY	0	1	2.5	5	10	Total
1						
Count	2	2	2	2	2	10
Sum	0.21	0.4	0.43	0.45	0.17	1.66
Average	0.105	0.2	0.215	0.225	0.085	0.166
Variance	0.00005	0.045	0.00045	0.00605	0.00605	0.010249
2						
Count	2	2	2	2	2	10
Sum	0.31	0.49	0.26	0.66	0.35	2.07
Average	0.155	0.245	0.13	0.33	0.175	0.207
Variance	0.00605	0.00125	0.0032	0.0392	5E-05	0.011357
3						
Count	2	2	2	2	2	10
Sum	0.34	0.26	0.4	0.44	0.3	1.74
Average	0.17	0.13	0.2	0.22	0.15	0.174
Variance	0.0098	0.0002	0.0032	0.0018	0	0.002849
Total						
Count	6	6	6	6	6	
Sum	0.86	1.15	1.09	1.55	0.82	
Average	0.143333	0.191667	0.181667	0.258333	0.136667	
Variance	0.004107	0.011977	0.003017	0.012497	0.002947	

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Sample	0.009447	2	0.004723	0.579076	0.572462	3.68232
Columns	0.05682	4	0.014205	1.74152	0.193312	3.055568
Interaction	0.04092	8	0.005115	0.627094	0.743364	2.640797
Within	0.12235	15	0.008157			
Total	0.229537	29				

C. Regression Analysis between Grass Species and Oil Concentration

A. stolonifera **, Harvest 1, fresh weight**

Regression Statistics	
Multiple R	0.685893
R Square	0.470449
Adjusted R Square	0.446379
Standard Error	3.022614
Observations	24

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	178.5639	178.5639	19.54466281	0.000216
Residual	22	200.9963	9.136195		
Total	23	379.5602			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	9.136902	0.930227	9.822227	1.67136E-09	7.207727	11.06608	7.207727	11.06608
oil conc	-1.448332	0.327608	-4.420935	0.000215766	-2.12775	-0.768915	-2.12775	-0.768915

A. stolonifera**, Harvest 1, dry weight**

Regression Statistics	
Multiple R	0.679442
R Square	0.461642
Adjusted R Square	0.437171
Standard Error	0.48648
Observations	24

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	4.464636	4.464636	18.865	0.000260782
Residual	22	5.206571	0.236662		
Total	23	9.671207			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	1.465116	0.149717	9.785907	1.79E-09	1.154621573	1.77561	1.154622	1.77561
oil conc	-0.229015	0.052727	-4.343386	0.000261	-0.338365236	-0.119665	-0.338365	-0.119665

F. rubra, Harvest 1, fresh weight

Regression Statistics	
Multiple R	0.807274
R Square	0.651692
Adjusted R Square	0.639252
Standard Error	0.628707
Observations	30

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	20.70776	20.70776	52.38857	7.04E-08
Residual	28	11.06763	0.395272		
Total	29	31.77539			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	2.282322	0.165263	13.81026	5.06E-14	1.943796	2.620848	1.943796	2.620848
oil conc	-0.23258	0.032134	-7.23799	7.04E-08	-0.29841	-0.16676	-0.29841	-0.16676

F. rubra, Harvest 1, dry weight

Regression Statistics	
Multiple R	0.784941
R Square	0.616132
Adjusted R Square	0.602423
Standard Error	0.137145
Observations	30

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.845304	0.845304	44.94181	2.82E-07
Residual	28	0.526648	0.018809		
Total	29	1.371953			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0.453802	0.03605	12.58806	4.78E-13	0.379957	0.527648	0.379957	0.527648
oil conc	-0.04699	0.00701	-6.70387	2.82E-07	-0.06135	-0.03263	-0.06135	-0.03263

***P. trivialis*, Harvest 1, fresh weight**

Regression Statistics	
Multiple R	0.802853
R Square	0.644574
Adjusted R Square	0.63188
Standard Error	2.285216
Observations	30

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	265.1769	265.1769	50.77863	9.39E-08
Residual	28	146.222	5.222213		
Total	29	411.3988			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	8.328844	0.600695	13.86534	4.59E-14	7.098374	9.559314	7.098374	9.559314
oil conc	-0.8323	0.1168	-7.12591	9.39E-08	-1.07156	-0.59305	-1.07156	-0.59305

***P. trivialis*, Harvest 1, dry weight**

Regression Statistics	
Multiple R	0.826263
R Square	0.68271
Adjusted R Square	0.671378
Standard Error	0.340154
Observations	30

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	6.970902	6.970902	60.24731	1.87E-08
Residual	28	3.239734	0.115705		
Total	29	10.21064			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	1.373382	0.089413	15.35991	3.6E-15	1.190227	1.556537	1.190227	1.556537
oil conc	-0.13495	0.017386	-7.76191	1.87E-08	-0.17056	-0.09933	-0.17056	-0.09933

***L. perenne*, Harvest 1, fresh weight**

Regression Statistics	
Multiple R	0.863119
R Square	0.744975
Adjusted R Square	0.735867
Standard Error	2.944738
Observations	30

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	709.2678	709.2678	81.79313	8.43E-10
Residual	28	242.8016	8.671484		
Total	29	952.0694			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	12.71712	0.774058	16.42915	6.57E-16	11.13153	14.30271	11.13153	14.30271
oil conc	-1.36119	0.150508	-9.04396	8.43E-10	-1.66949	-1.05289	-1.66949	-1.05289

***L. perenne*, Harvest 1, dry weight**

Regression Statistics	
Multiple R	0.865651
R Square	0.749351
Adjusted R Square	0.7404
Standard Error	0.453168
Observations	30

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	17.19079	17.19079	83.71017	6.6E-10
Residual	28	5.750105	0.205361		
Total	29	22.9409			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	2.026706	0.11912	17.01394	2.69E-16	1.782699	2.270713	1.782699	2.270713
oil conc	-0.21192	0.023162	-9.14933	6.6E-10	-0.25936	-0.16447	-0.25936	-0.16447

***A. stolonifera*, Harvest 2, fresh weight**

Regression Statistics	
Multiple R	0.715255
R Square	0.51159
Adjusted R Square	0.489389
Standard Error	1.364069
Observations	24

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	42.87778	42.87778	23.0441	8.55E-05
Residual	22	40.93504	1.860684		
Total	23	83.81282			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	5.979619	0.4198	14.24397	1.38E-12	5.109006	6.850232	5.109006	6.850232
oil conc	-0.70972	0.147845	-4.80043	8.55E-05	-1.01633	-0.40311	-1.01633	-0.40311

***A. stolonifera*, Harvest 2, dry weight**

Regression Statistics	
Multiple R	0.72226
R Square	0.521659
Adjusted R Square	0.499917
Standard Error	0.328887
Observations	24

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	2.595171	2.595171	23.99234	6.74E-05
Residual	22	2.379667	0.108167		
Total	23	4.974839			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	1.428959	0.101217	14.11779	1.65E-12	1.219047	1.63887	1.219047	1.63887
oil conc	-0.1746	0.035647	-4.8982	6.74E-05	-0.24853	-0.10068	-0.24853	-0.10068

***F. rubra*, Harvest 2, fresh weight**

Regression Statistics	
Multiple R	0.83467
R Square	0.696675
Adjusted R Square	0.685842
Standard Error	1.148483
Observations	30

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	84.82594	84.82594	64.31013	9.85E-09
Residual	28	36.93238	1.319014		
Total	29	121.7583			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	4.409034	0.301892	14.60467	1.27E-14	3.790635	5.027432	3.790635	5.027432
oil conc	-0.47074	0.0587	-8.01936	9.85E-09	-0.59098	-0.3505	-0.59098	-0.3505

***F. rubra*, Harvest 2, dry weight**

Regression Statistics	
Multiple R	0.857195
R Square	0.734784
Adjusted R Square	0.725312
Standard Error	0.332787
Observations	30

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	8.591129	8.591129	77.57429	1.47E-09
Residual	28	3.100919	0.110747		
Total	29	11.69205			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	1.400312	0.087477	16.0078	1.27E-15	1.221123	1.5795	1.221123	1.5795
oil conc	-0.14981	0.017009	-8.80763	1.47E-09	-0.18465	-0.11497	-0.18465	-0.11497

***P. trivialis*, Harvest 2, fresh weight**

Regression Statistics	
Multiple R	0.476411
R Square	0.226967
Adjusted R Square	0.19183
Standard Error	1.480756
Observations	24

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	14.16301	14.16301	6.459342	0.018596
Residual	22	48.23807	2.192639		
Total	23	62.40107			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	5.923887	0.455711	12.99921	8.43E-12	4.978798	6.868975	4.978798	6.868975
oil conc	-0.4079	0.160493	-2.54152	0.018596	-0.74074	-0.07505	-0.74074	-0.07505

***P. trivialis*, Harvest 2, dry weight**

Regression Statistics	
Multiple R	0.457214
R Square	0.209045
Adjusted R Square	0.173092
Standard Error	0.393867
Observations	24

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.902007	0.902007	5.814477	0.024687
Residual	22	3.412889	0.155131		
Total	23	4.314896			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	1.553148	0.121215	12.81318	1.12E-11	1.301763	1.804532	1.301763	1.804532
oil conc	-0.10294	0.04269	-2.41132	0.024687	-0.19147	-0.01441	-0.19147	-0.01441

L. perenne, Harvest 2, fresh weight

Regression Statistics	
Multiple R	0.85545
R Square	0.731795
Adjusted R Square	0.722216
Standard Error	1.517187
Observations	30

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	175.8565	175.8565	76.39768	1.72E-09
Residual	28	64.452	2.301857		
Total	29	240.3085			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	7.072529	0.39881	17.73408	9.26E-17	6.255603	7.889455	6.255603	7.889455
oil conc	-0.67779	0.077545	-8.74058	1.72E-09	-0.83663	-0.51894	-0.83663	-0.51894

L. perenne, Harvest 2, dry weight

Regression Statistics	
Multiple R	0.85291
R Square	0.727455
Adjusted R Square	0.717721
Standard Error	0.372649
Observations	30

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	10.37826	10.37826	74.73519	2.16E-09
Residual	28	3.888279	0.138867		
Total	29	14.26654			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	1.727939	0.097955	17.64013	1.06E-16	1.527287	1.928591	1.527287	1.928591
oil conc	-0.16466	0.019046	-8.64495	2.16E-09	-0.20367	-0.12564	-0.20367	-0.12564

***A. stolonifera*, Harvest 3, fresh weight**

Regression Statistics	
Multiple R	0.642902
R Square	0.413322
Adjusted R Square	0.39237
Standard Error	0.877535
Observations	30

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	15.19065	15.19065	19.72639	0.000127
Residual	28	21.56189	0.770068		
Total	29	36.75254			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	2.864915	0.23067	12.41997	6.59E-13	2.392408	3.337422	2.392408	3.337422
oil conc	-0.19921	0.044852	-4.44144	0.000127	-0.29108	-0.10733	-0.29108	-0.10733

***A. stolonifera*, Harvest 3, dry weight**

Regression Statistics	
Multiple R	0.655237
R Square	0.429335
Adjusted R Square	0.408954
Standard Error	0.191202
Observations	30

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.770118	0.770118	21.06559	8.51E-05
Residual	28	1.023626	0.036558		
Total	29	1.793744			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0.60131	0.05026	11.96409	1.6E-12	0.498358	0.704262	0.498358	0.704262
oil conc	-0.04485	0.009773	-4.58973	8.51E-05	-0.06487	-0.02484	-0.06487	-0.02484

F. rubra, Harvest 3, fresh weight

Regression Statistics	
Multiple R	0.761537
R Square	0.579939
Adjusted R Square	0.564936
Standard Error	0.669128
Observations	30

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	17.30794	17.30794	38.65692	1.02E-06
Residual	28	12.53649	0.447732		
Total	29	29.84443			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	2.661343	0.175888	15.13091	5.25E-15	2.301053	3.021633	2.301053	3.021633
oil conc	-0.21264	0.0342	-6.21747	1.02E-06	-0.28269	-0.14258	-0.28269	-0.14258

F. rubra, Harvest 3, dry weight

Regression Statistics	
Multiple R	0.764142
R Square	0.583912
Adjusted R Square	0.569052
Standard Error	0.169168
Observations	30

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	1.124495	1.124495	39.29351	8.91E-07
Residual	28	0.801299	0.028618		
Total	29	1.925794			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0.65327	0.044468	14.69088	1.1E-14	0.562182	0.744359	0.562182	0.744359
oil conc	-0.0542	0.008646	-6.26845	8.91E-07	-0.07191	-0.03649	-0.07191	-0.03649

***P. trivialis*, Harvest 3, fresh weight**

Regression Statistics	
Multiple R	0.717117
R Square	0.514256
Adjusted R Square	0.496908
Standard Error	0.667746
Observations	30

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	13.2176	13.2176	29.64357	8.24E-06
Residual	28	12.48476	0.445884		
Total	29	25.70237			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	2.532257	0.175525	14.42679	1.72E-14	2.172711	2.891804	2.172711	2.891804
oil conc	-0.18582	0.034129	-5.44459	8.24E-06	-0.25573	-0.11591	-0.25573	-0.11591

***P. trivialis*, Harvest 3, dry weight**

Regression Statistics	
Multiple R	0.722769
R Square	0.522395
Adjusted R Square	0.505338
Standard Error	0.168323
Observations	30

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.867706	0.867706	30.62586	6.46E-06
Residual	28	0.793309	0.028332		
Total	29	1.661015			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0.603708	0.044245	13.64451	6.8E-14	0.513075	0.694341	0.513075	0.694341
oil conc	-0.04761	0.008603	-5.53406	6.46E-06	-0.06523	-0.02999	-0.06523	-0.02999

***L. perenne*, Harvest 3, fresh weight**

Regression Statistics	
Multiple R	0.749257
R Square	0.561386
Adjusted R Square	0.545721
Standard Error	0.837144
Observations	30

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	25.11524	25.11524	35.83739	1.9E-06
Residual	28	19.62271	0.700811		
Total	29	44.73794			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	3.528843	0.220053	16.03633	1.21E-15	3.078084	3.979601	3.078084	3.979601
oil conc	-0.25614	0.042787	-5.98643	1.9E-06	-0.34379	-0.1685	-0.34379	-0.1685

***L. perenne*, Harvest 3, dry weight**

Regression Statistics	
Multiple R	0.789606
R Square	0.623478
Adjusted R Square	0.610031
Standard Error	0.172389
Observations	30

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	1.37786	1.37786	46.36482	2.14E-07
Residual	28	0.832098	0.029718		
Total	29	2.209959			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0.770202	0.045314	16.9969	2.76E-16	0.67738	0.863025	0.67738	0.863025
oil conc	-0.06	0.008811	-6.80917	2.14E-07	-0.07804	-0.04195	-0.07804	-0.04195

***A. stolonifera*, Harvest 4, fresh weight**

Regression Statistics	
Multiple R	0.506522
R Square	0.256565
Adjusted R Square	0.230014
Standard Error	0.428465
Observations	30

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	1.773959	1.773959	9.663005	0.004287
Residual	28	5.140311	0.183583		
Total	29	6.91427			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	1.460876	0.112627	12.97092	2.33E-13	1.23017	1.691583	1.23017	1.691583
oil conc	-0.06807	0.021899	-3.10854	0.004287	-0.11293	-0.02322	-0.11293	-0.02322

***A. stolonifera*, Harvest 4, dry weight**

Regression Statistics	
Multiple R	0.60159
R Square	0.36191
Adjusted R Square	0.339121
Standard Error	0.105169
Observations	30

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.175653	0.175653	15.88097	0.000437
Residual	28	0.309697	0.011061		
Total	29	0.48535			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0.394258	0.027645	14.26147	2.29E-14	0.33763	0.450886	0.33763	0.450886
oil conc	-0.02142	0.005375	-3.98509	0.000437	-0.03243	-0.01041	-0.03243	-0.01041

***F. rubra*, Harvest 4, fresh weight**

Regression Statistics	
Multiple R	0.662317
R Square	0.438663
Adjusted R Square	0.418616
Standard Error	0.478777
Observations	30

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	5.015719	5.015719	21.88094	6.69E-05
Residual	28	6.418378	0.229228		
Total	29	11.4341			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	1.603195	0.125852	12.73872	3.59E-13	1.345398	1.860992	1.345398	1.860992
oil conc	-0.11447	0.024471	-4.67771	6.69E-05	-0.16459	-0.06434	-0.16459	-0.06434

***F. rubra*, Harvest 4, dry weight**

Regression Statistics	
Multiple R	0.676619
R Square	0.457813
Adjusted R Square	0.438449
Standard Error	0.119884
Observations	30

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.339796	0.339796	23.64268	4.04E-05
Residual	28	0.40242	0.014372		
Total	29	0.742217			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0.411903	0.031513	13.07095	1.93E-13	0.347352	0.476454	0.347352	0.476454
oil conc	-0.02979	0.006127	-4.86237	4.04E-05	-0.04235	-0.01724	-0.04235	-0.01724

***P. trivialis*, Harvest 4, fresh weight**

Regression Statistics	
Multiple R	0.562767
R Square	0.316707
Adjusted R Square	0.292304
Standard Error	0.481656
Observations	30

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	3.010801	3.010801	12.97802	0.001206
Residual	28	6.495786	0.231992		
Total	29	9.506587			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	1.475472	0.126609	11.65379	2.96E-12	1.216125	1.734818	1.216125	1.734818
oil conc	-0.08869	0.024618	-3.6025	0.001206	-0.13911	-0.03826	-0.13911	-0.03826

***P. trivialis*, Harvest 4, dry weight**

Regression Statistics	
Multiple R	0.609063
R Square	0.370957
Adjusted R Square	0.348491
Standard Error	0.123064
Observations	30

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.25007	0.25007	16.51207	0.000354
Residual	28	0.42405	0.015145		
Total	29	0.67412			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0.418568	0.032349	12.93927	2.47E-13	0.352305	0.484832	0.352305	0.484832
oil conc	-0.02556	0.00629	-4.0635	0.000354	-0.03844	-0.01267	-0.03844	-0.01267

***L. perenne*, Harvest 4, fresh weight**

Regression Statistics	
Multiple R	0.609094
R Square	0.370996
Adjusted R Square	0.348532
Standard Error	0.545666
Observations	30

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	4.917307	4.917307	16.51482	0.000354
Residual	28	8.33703	0.297751		
Total	29	13.25434			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	1.963686	0.143434	13.69047	6.26E-14	1.669873	2.257499	1.669873	2.257499
oil conc	-0.11334	0.027889	-4.06384	0.000354	-0.17047	-0.05621	-0.17047	-0.05621

***L. perenne*, Harvest 4, dry weight**

Regression Statistics	
Multiple R	0.674838
R Square	0.455406
Adjusted R Square	0.435957
Standard Error	0.118587
Observations	30

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.329273	0.329273	23.41449	4.31E-05
Residual	28	0.393757	0.014063		
Total	29	0.72303			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0.475516	0.031172	15.25467	4.28E-15	0.411663	0.539369	0.411663	0.539369
oil conc	-0.02933	0.006061	-4.83885	4.31E-05	-0.04174	-0.01691	-0.04174	-0.01691

A. stolonifera, Harvest 5, fresh weight

Regression Statistics	
Multiple R	0.308206
R Square	0.094991
Adjusted R Square	0.062669
Standard Error	0.451057
Observations	30

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.597927	0.597927	2.93891	0.09752
Residual	28	5.696659	0.203452		
Total	29	6.294587			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0.893102	0.118565	7.53257	3.32E-08	0.650232	1.135973	0.650232	1.135973
oil conc	0.039522	0.023054	1.714325	0.09752	-0.0077	0.086746	-0.0077	0.086746

A. stolonifera, Harvest 5, dry weight

Regression Statistics	
Multiple R	0.225251
R Square	0.050738
Adjusted R Square	0.016836
Standard Error	0.11577
Observations	30

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.020059	0.020059	1.496601	0.231391
Residual	28	0.375278	0.013403		
Total	29	0.395337			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0.228883	0.030432	7.521242	3.42E-08	0.166547	0.29122	0.166547	0.29122
oil conc	0.007239	0.005917	1.223356	0.231391	-0.00488	0.019359	-0.00488	0.019359

***F. rubra*, Harvest 5, fresh weight**

Regression Statistics	
Multiple R	0.547716
R Square	0.299992
Adjusted R Square	0.274992
Standard Error	0.366581
Observations	30

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	1.612524	1.612524	11.99956	0.001731
Residual	28	3.762693	0.134382		
Total	29	5.375217			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	1.218476	0.09636	12.64502	4.29E-13	1.021091	1.415861	1.021091	1.415861
oil conc	-0.0649	0.018736	-3.46404	0.001731	-0.10328	-0.02652	-0.10328	-0.02652

***F. rubra*, Harvest 5, dry weight**

Regression Statistics	
Multiple R	0.53694
R Square	0.288304
Adjusted R Square	0.262886
Standard Error	0.099919
Observations	30

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.113242	0.113242	11.34265	0.002219
Residual	28	0.279545	0.009984		
Total	29	0.392787			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0.284305	0.026265	10.82458	1.63E-11	0.230504	0.338106	0.230504	0.338106
oil conc	-0.0172	0.005107	-3.36789	0.002219	-0.02766	-0.00674	-0.02766	-0.00674

***P. trivialis*, Harvest 5, fresh weight**

Regression Statistics	
Multiple R	0.215186
R Square	0.046305
Adjusted R Square	0.012244
Standard Error	0.438663
Observations	30

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.261599	0.261599	1.359485	0.253463
Residual	28	5.387898	0.192425		
Total	29	5.649497			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	1.077057	0.115307	9.340739	4.24E-10	0.84086	1.313254	0.84086	1.313254
oil conc	-0.02614	0.02242	-1.16597	0.253463	-0.07207	0.019785	-0.07207	0.019785

***P. trivialis*, Harvest 5, dry weight**

Regression Statistics	
Multiple R	0.256143
R Square	0.065609
Adjusted R Square	0.032238
Standard Error	0.115041
Observations	30

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.02602	0.02602	1.966045	0.171858
Residual	28	0.370567	0.013235		
Total	29	0.396587			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0.273171	0.03024	9.033457	8.64E-10	0.211228	0.335115	0.211228	0.335115
oil conc	-0.00824	0.00588	-1.40216	0.171858	-0.02029	0.0038	-0.02029	0.0038

***L. perenne*, Harvest 5, fresh weight**

Regression Statistics	
Multiple R	0.745617
R Square	0.555944
Adjusted R Square	0.542884
Standard Error	0.400423
Observations	36

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	6.825119	6.825119	42.56699	1.81E-07
Residual	34	5.451503	0.160338		
Total	35	12.27662			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	1.453014	0.091168	15.9377	2.42E-17	1.267737	1.63829	1.267737	1.63829
oil conc	-0.06315	0.00968	-6.52434	1.81E-07	-0.08283	-0.04348	-0.08283	-0.04348

***L. perenne*, Harvest 5, dry weight**

Regression Statistics	
Multiple R	0.750091
R Square	0.562637
Adjusted R Square	0.549773
Standard Error	0.095197
Observations	36

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.396376	0.396376	43.73861	1.39E-07
Residual	34	0.308121	0.009062		
Total	35	0.704497			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0.337935	0.021674	15.59147	4.68E-17	0.293888	0.381983	0.293888	0.381983
oil conc	-0.01522	0.002301	-6.61352	1.39E-07	-0.0199	-0.01054	-0.0199	-0.01054

A. stolonifera, Harvest 6, fresh weight

Regression Statistics	
Multiple R	0.571225
R Square	0.326299
Adjusted R Square	0.302238
Standard Error	0.222482
Observations	30

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.671267	0.671267	13.56143	0.000977
Residual	28	1.38595	0.049498		
Total	29	2.057217			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	1.023393	0.058482	17.49931	1.31E-16	0.903598	1.143188	0.903598	1.143188
oil conc	0.041876	0.011371	3.682585	0.000977	0.018583	0.065169	0.018583	0.065169

A. stolonifera, Harvest 6, dry weight

Regression Statistics	
Multiple R	0.591963
R Square	0.35042
Adjusted R Square	0.32722
Standard Error	0.056418
Observations	30

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.048078	0.048078	15.10476	0.000569
Residual	28	0.089122	0.003183		
Total	29	0.1372			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0.138534	0.01483	9.341499	4.24E-10	0.108157	0.168912	0.108157	0.168912
oil conc	0.011207	0.002884	3.886484	0.000569	0.0053	0.017114	0.0053	0.017114

F. rubra, Harvest 6, fresh weight

Regression Statistics	
Multiple R	0.305088
R Square	0.093078
Adjusted R Square	0.060688
Standard Error	0.556941
Observations	30

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.891366	0.891366	2.873674	0.101134
Residual	28	8.685131	0.310183		
Total	29	9.576497			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	1.278877	0.146398	8.735598	1.74E-09	0.978993	1.57876	0.978993	1.57876
oil conc	-0.04825	0.028466	-1.69519	0.101134	-0.10656	0.010055	-0.10656	0.010055

F. rubra, Harvest 6, dry weight

Regression Statistics	
Multiple R	0.283086
R Square	0.080137
Adjusted R Square	0.047285
Standard Error	0.10148
Observations	30

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.025121	0.025121	2.439331	0.12956
Residual	28	0.288349	0.010298		
Total	29	0.31347			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0.180973	0.026675	6.784326	2.28E-07	0.126331	0.235615	0.126331	0.235615
oil conc	-0.0081	0.005187	-1.56184	0.12956	-0.01873	0.002524	-0.01873	0.002524

***P. trivialis*, Harvest 6, fresh weight**

Regression Statistics	
Multiple R	0.218542
R Square	0.047761
Adjusted R Square	0.013752
Standard Error	0.391312
Observations	30

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.215045	0.215045	1.404377	0.245953
Residual	28	4.287501	0.153125		
Total	29	4.502547			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	1.12903	0.102861	10.97628	1.18E-11	0.918328	1.339731	0.918328	1.339731
oil conc	-0.0237	0.02	-1.18506	0.245953	-0.06467	0.017267	-0.06467	0.017267

***P. trivialis*, Harvest 6, dry weight**

Regression Statistics	
Multiple R	0.001286
R Square	1.65E-06
Adjusted R Square	-0.03571
Standard Error	0.090164
Observations	30

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	3.76E-07	3.76E-07	4.63E-05	0.994621
Residual	28	0.22763	0.00813		
Total	29	0.22763			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0.152884	0.023701	6.450596	5.49E-07	0.104335	0.201433	0.104335	0.201433
oil conc	3.13E-05	0.004608	0.006802	0.994621	-0.00941	0.009471	-0.00941	0.009471

L. perenne, Harvest 6, fresh weight

Regression Statistics	
Multiple R	0.082826
R Square	0.00686
Adjusted R Square	-0.02861
Standard Error	0.464987
Observations	30

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.041818	0.041818	0.193412	0.663468
Residual	28	6.053968	0.216213		
Total	29	6.095787			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	1.231339	0.122227	10.07418	8.17E-11	0.980967	1.48171	0.980967	1.48171
oil conc	-0.01045	0.023766	-0.43979	0.663468	-0.05913	0.03823	-0.05913	0.03823

L. perenne, Harvest 6, dry weight

Regression Statistics	
Multiple R	0.044166
R Square	0.001951
Adjusted R Square	-0.03369
Standard Error	0.090453
Observations	30

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.000448	0.000448	0.054725	0.816739
Residual	28	0.229089	0.008182		
Total	29	0.229537			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0.186335	0.023777	7.8369	1.55E-08	0.137631	0.235039	0.137631	0.235039
oil conc	-0.00108	0.004623	-0.23393	0.816739	-0.01055	0.008389	-0.01055	0.008389

D. Cumulative Weight Summaries

Cumulative weight summary of *A. stolonifera* L., from harvests during a six-month period (fresh sample data)

Harvest	0%	1%	2.5%	5%	10%	20%
1	116.22g	83.00g	80.94g	36.84g	2.82g	0.00g
2	196.38g	150.63g	145.55g	81.23g	28.11g	0.00g
3	237.38g	199.50g	193.47g	127.54g	55.14g	0.00g
4	270.83g	235.99g	228.73g	165.54g	82.87g	0.00g
5	300.79g	268.72g	259.72g	203.44g	116.66g	24.53g
6	333.27g	303.95g	292.20g	239.61g	153.21g	48.98g

Cumulative weight summary of *F. rubra* L., from harvests during a six-month period (fresh sample data)

Harvest	0%	1%	2.5%	5%	10%	20%
1	49.48g	39.53g	35.73g	30.48g	21.71g	0.00g
2	119.37g	94.04g	90.68g	64.38g	46.65g	0.00g
3	162.86g	138.71g	137.78g	106.81g	71.81g	0.00g
4	198.02g	175.42g	175.49g	143.30g	97.48g	0.00g
5	231.52g	209.11g	209.70g	177.27g	125.64g	0.00g
6	268.03g	244.75g	245.67g	213.60g	154.98g	0.00g

Cumulative weight summary of *P. trivialis* L., from harvests during a six-month period (fresh sample data)

Harvest	0%	1%	2.5%	5%	10%	20%
1	113.84g	79.71g	74.06g	58.75g	25.68g	0.00g
2	189.57g	155.31g	139.59g	114.81g	51.97g	0.00g
3	230.23g	202.86g	183.10g	157.47g	79.09g	0.00g
4	262.45g	242.23g	219.83g	192.17g	106.36g	0.00g
5	293.04g	277.20g	252.63g	226.23g	136.60g	0.00g
6	325.85g	313.16g	284.33g	262.76g	166.63g	0.00g

Cumulative weight summary of *L. perenne* L., from harvests during a six-month period (fresh sample data)

Harvest	0%	1%	2.5%	5%	10%	20%
1	162.67g	111.29g	97.29g	54.43g	29.61g	25.82g
2	249.14g	190.94g	173.17g	102.39g	58.19g	51.32g
3	297.93g	245.15g	230.32g	144.22g	89.40g	76.72g
4	333.69g	286.76g	274.21g	182.10g	118.10g	101.10g
5	366.56g	322.90g	310.64g	217.84g	148.60g	125.63g
6	399.84g	358.02g	345.03g	255.09g	180.55g	150.72g

Appendix II VPS Field Trial

A. One-Way ANOVA for Compaction and Elements across the VPS

ANOVA

Compaction

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	66.466	5	13.293	45.023	.000
Within Groups	129.911	440	.295		
Total	196.377	445			

Al

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	1995.686	5	399.137	5.997	.000
Within Groups	29284.103	440	66.555		
Total	31279.789	445			

Ca

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	2209.583	5	441.917	9.154	.000
Within Groups	21241.365	440	48.276		
Total	23450.948	445			

Cr

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	.096	5	.019	12.566	.000
Within Groups	.674	440	.002		
Total	.770	445			

Cu

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	.082	5	.016	3.600	.003
Within Groups	2.009	440	.005		
Total	2.091	445			

One-Way ANOVA for Compaction and Elements across the VPS (continued)

K

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	79.526	5	15.905	10.731	.000
Within Groups	652.130	440	1.482		
Total	731.656	445			

Mg

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	135.581	5	27.116	9.988	.000
Within Groups	1194.491	440	2.715		
Total	1330.073	445			

Mo

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	.000	5	.000	.907	.476
Within Groups	.025	440	.000		
Total	.025	445			

P

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	7.657	5	1.531	3.197	.008
Within Groups	210.790	440	.479		
Total	218.447	445			

Pb

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	.144	5	.029	7.698	.000
Within Groups	1.642	440	.004		
Total	1.785	445			

One-Way ANOVA for Compaction and Elements across the VPS (continued)

Zn

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	3.374	5	.675	2.850	.015
Within Groups	104.177	440	.237		
Total	107.551	445			

B. One-way ANOVA: Aluminium between bays

Al
Tukey HSD

(I) Bay	(J) Bay	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
0	1	-3.8437169	1.8048021	.274	-9.009646	1.322212
	2	-3.4645679	1.8129136	.397	-8.653714	1.724578
	3	1.2180577	1.7996902	.984	-3.933239	6.369354
	4	1.0319902	1.8074448	.993	-4.141503	6.205483
	5	-.3903486	1.8022179	1.000	-5.548880	4.768183
1	0	3.8437169	1.8048021	.274	-1.322212	9.009646
	2	.3791490	1.2704262	1.000	-3.257223	4.015521
	3	5.0617746*	1.2514838	.001	1.479622	8.643927
	4	4.8757071*	1.2626099	.002	1.261708	8.489706
	5	3.4533683	1.2551160	.068	-.139181	7.045917
2	0	3.4645679	1.8129136	.397	-1.724578	8.653714
	1	-.3791490	1.2704262	1.000	-4.015521	3.257223
	3	4.6826256*	1.2631535	.003	1.067071	8.298180
	4	4.4965581*	1.2741777	.006	.849449	8.143668
	5	3.0742193	1.2667523	.149	-.551636	6.700075
3	0	-1.2180577	1.7996902	.984	-6.369354	3.933239
	1	-5.0617746*	1.2514838	.001	-8.643927	-1.479622
	2	-4.6826256*	1.2631535	.003	-8.298180	-1.067071
	4	-.1860675	1.2552918	1.000	-3.779120	3.406985
	5	-1.6084063	1.2477541	.791	-5.179883	1.963070
4	0	-1.0319902	1.8074448	.993	-6.205483	4.141503
	1	-4.8757071*	1.2626099	.002	-8.489706	-1.261708
	2	-4.4965581*	1.2741777	.006	-8.143668	-.849449
	3	.1860675	1.2552918	1.000	-3.406985	3.779120
	5	-1.4223388	1.2589131	.869	-5.025756	2.181079
5	0	.3903486	1.8022179	1.000	-4.768183	5.548880
	1	-3.4533683	1.2551160	.068	-7.045917	.139181
	2	-3.0742193	1.2667523	.149	-6.700075	.551636
	3	1.6084063	1.2477541	.791	-1.963070	5.179883
	4	1.4223388	1.2589131	.869	-2.181079	5.025756

*. The mean difference is significant at the 0.05 level.

One-way ANOVA: Calcium between bays

Ca
Tukey HSD

(I) Bay	(J) Bay	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
0	1	1.1071561	1.5371096	.979	-3.292550	5.506862
	2	.7117284	1.5440180	.997	-3.707752	5.131208
	3	3.4656417	1.5327559	.212	-.921602	7.852886
	4	2.1496876	1.5393603	.729	-2.256460	6.555836
	5	-3.2896688	1.5349087	.267	-7.683075	1.103737
1	0	-1.1071561	1.5371096	.979	-5.506862	3.292550
	2	-.3954277	1.0819936	.999	-3.492444	2.701589
	3	2.3584856	1.0658607	.234	-.692353	5.409324
	4	1.0425316	1.0753366	.927	-2.035430	4.120493
	5	-4.3968249*	1.0689542	.001	-7.456518	-1.337131
2	0	-.7117284	1.5440180	.997	-5.131208	3.707752
	1	.3954277	1.0819936	.999	-2.701589	3.492444
	3	2.7539133	1.0757996	.110	-.325374	5.833200
	4	1.4379592	1.0851886	.771	-1.668202	4.544121
	5	-4.0013972*	1.0788646	.003	-7.089457	-.913337
3	0	-3.4656417	1.5327559	.212	-7.852886	.921602
	1	-2.3584856	1.0658607	.234	-5.409324	.692353
	2	-2.7539133	1.0757996	.110	-5.833200	.325374
	4	-1.3159540	1.0691040	.822	-4.376076	1.744168
	5	-6.7553105*	1.0626842	.000	-9.797057	-3.713564
4	0	-2.1496876	1.5393603	.729	-6.555836	2.256460
	1	-1.0425316	1.0753366	.927	-4.120493	2.035430
	2	-1.4379592	1.0851886	.771	-4.544121	1.668202
	3	1.3159540	1.0691040	.822	-1.744168	4.376076
	5	-5.4393565*	1.0721881	.000	-8.508306	-2.370407
5	0	3.2896688	1.5349087	.267	-1.103737	7.683075
	1	4.3968249*	1.0689542	.001	1.337131	7.456518
	2	4.0013972*	1.0788646	.003	.913337	7.089457
	3	6.7553105*	1.0626842	.000	3.713564	9.797057
	4	5.4393565*	1.0721881	.000	2.370407	8.508306

*. The mean difference is significant at the 0.05 level.

One-way ANOVA: Chromium between bays

Cr
Tukey HSD

(I) Bay	(J) Bay	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
0	1	-.0145397	.0086590	.546	-.039325	.010245
	2	.0077160	.0086980	.950	-.017180	.032612
	3	-.0103902	.0086345	.835	-.035105	.014325
	4	-.0227858	.0086717	.093	-.047607	.002035
	5	-.0371111*	.0086466	.000	-.061861	-.012362
1	0	.0145397	.0086590	.546	-.010245	.039325
	2	.0222557*	.0060952	.004	.004809	.039702
	3	.0041495	.0060043	.983	-.013037	.021336
	4	-.0082461	.0060577	.750	-.025585	.009093
	5	-.0225714*	.0060218	.003	-.039808	-.005335
2	0	-.0077160	.0086980	.950	-.032612	.017180
	1	-.0222557*	.0060952	.004	-.039702	-.004809
	3	-.0181062*	.0060603	.035	-.035453	-.000760
	4	-.0305019*	.0061132	.000	-.048000	-.013004
	5	-.0448272*	.0060776	.000	-.062223	-.027431
3	0	.0103902	.0086345	.835	-.014325	.035105
	1	-.0041495	.0060043	.983	-.021336	.013037
	2	.0181062*	.0060603	.035	.000760	.035453
	4	-.0123956	.0060226	.311	-.029634	.004843
	5	-.0267209*	.0059865	.000	-.043856	-.009586
4	0	.0227858	.0086717	.093	-.002035	.047607
	1	.0082461	.0060577	.750	-.009093	.025585
	2	.0305019*	.0061132	.000	.013004	.048000
	3	.0123956	.0060226	.311	-.004843	.029634
	5	-.0143253	.0060400	.169	-.031614	.002963
5	0	.0371111*	.0086466	.000	.012362	.061861
	1	.0225714*	.0060218	.003	.005335	.039808
	2	.0448272*	.0060776	.000	.027431	.062223
	3	.0267209*	.0059865	.000	.009586	.043856
	4	.0143253	.0060400	.169	-.002963	.031614

*. The mean difference is significant at the 0.05 level.

One-way ANOVA: Copper between bays

Cu
Tukey HSD

(I) Bay	(J) Bay	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
0	1	-.0127831	.0149491	.957	-.055572	.030006
	2	-.0070000	.0150163	.997	-.049981	.035981
	3	.0152214	.0149068	.911	-.027447	.057889
	4	-.0095203	.0149710	.988	-.052372	.033332
	5	-.0273808	.0149277	.445	-.070109	.015347
1	0	.0127831	.0149491	.957	-.030006	.055572
	2	.0057831	.0105229	.994	-.024337	.035903
	3	.0280044	.0103660	.077	-.001666	.057675
	4	.0032628	.0104581	1.000	-.026672	.033197
	5	-.0145978	.0103961	.725	-.044355	.015159
2	0	.0070000	.0150163	.997	-.035981	.049981
	1	-.0057831	.0105229	.994	-.035903	.024337
	3	.0222214	.0104626	.277	-.007726	.052169
	4	-.0025203	.0105540	1.000	-.032729	.027689
	5	-.0203808	.0104925	.378	-.050414	.009652
3	0	-.0152214	.0149068	.911	-.057889	.027447
	1	-.0280044	.0103660	.077	-.057675	.001666
	2	-.0222214	.0104626	.277	-.052169	.007726
	4	-.0247417	.0103975	.166	-.054503	.005019
	5	-.0426022*	.0103351	.001	-.072185	-.013020
4	0	.0095203	.0149710	.988	-.033332	.052372
	1	-.0032628	.0104581	1.000	-.033197	.026672
	2	.0025203	.0105540	1.000	-.027689	.032729
	3	.0247417	.0103975	.166	-.005019	.054503
	5	-.0178605	.0104275	.524	-.047707	.011986
5	0	.0273808	.0149277	.445	-.015347	.070109
	1	.0145978	.0103961	.725	-.015159	.044355
	2	.0203808	.0104925	.378	-.009652	.050414
	3	.0426022*	.0103351	.001	.013020	.072185
	4	.0178605	.0104275	.524	-.011986	.047707

*. The mean difference is significant at the 0.05 level.

One-way ANOVA: Potassium between bays

K
Tukey HSD

(I) Bay	(J) Bay	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
0	1	-.3504524	.2693276	.784	-1.121355	.420450
	2	-.4922716	.2705380	.454	-1.266639	.282096
	3	.3760426	.2685647	.727	-.392677	1.144762
	4	.5636586	.2697219	.294	-.208373	1.335690
	5	.4327333	.2689419	.593	-.337066	1.202532
1	0	.3504524	.2693276	.784	-.420450	1.121355
	2	-.1418192	.1895836	.976	-.684469	.400830
	3	.7264950*	.1867568	.002	.191936	1.261054
	4	.9141110*	.1884171	.000	.374800	1.453422
	5	.7831857*	.1872989	.000	.247076	1.319296
2	0	.4922716	.2705380	.454	-.282096	1.266639
	1	.1418192	.1895836	.976	-.400830	.684469
	3	.8683142*	.1884983	.000	.328771	1.407857
	4	1.0559302*	.1901434	.000	.511678	1.600182
	5	.9250049*	.1890353	.000	.383925	1.466085
3	0	-.3760426	.2685647	.727	-1.144762	.392677
	1	-.7264950*	.1867568	.002	-1.261054	-.191936
	2	-.8683142*	.1884983	.000	-1.407857	-.328771
	4	.1876160	.1873251	.917	-.348569	.723801
	5	.0566907	.1862002	1.000	-.476275	.589656
4	0	-.5636586	.2697219	.294	-1.335690	.208373
	1	-.9141110*	.1884171	.000	-1.453422	-.374800
	2	-1.0559302*	.1901434	.000	-1.600182	-.511678
	3	-.1876160	.1873251	.917	-.723801	.348569
	5	-.1309253	.1878655	.982	-.668657	.406807
5	0	-.4327333	.2689419	.593	-1.202532	.337066
	1	-.7831857*	.1872989	.000	-1.319296	-.247076
	2	-.9250049*	.1890353	.000	-1.466085	-.383925
	3	-.0566907	.1862002	1.000	-.589656	.476275
	4	.1309253	.1878655	.982	-.406807	.668657

*. The mean difference is significant at the 0.05 level.

One-way ANOVA: Magnesium between bays

Mg
Tukey HSD

(I) Bay	(J) Bay	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	Upper Bound
0	1	-1.3070714*	.3645064	.005	-2.350407	-.263736
	2	-1.2542469*	.3661446	.009	-2.302271	-.206222
	3	.0313721	.3634739	1.000	-1.009008	1.071752
	4	-.2678193	.3650401	.978	-1.312682	.777044
	5	-.9427882	.3639844	.102	-1.984630	.099053
1	0	1.3070714*	.3645064	.005	.263736	2.350407
	2	.0528245	.2565813	1.000	-.681594	.787243
	3	1.3384435*	.2527556	.000	.614975	2.061912
	4	1.0392522*	.2550026	.001	.309352	1.769152
	5	.3642832	.2534892	.704	-.361285	1.089851
2	0	1.2542469*	.3661446	.009	.206222	2.302271
	1	-.0528245	.2565813	1.000	-.787243	.681594
	3	1.2856190*	.2551124	.000	.555405	2.015834
	4	.9864276*	.2573389	.002	.249840	1.723015
	5	.3114587	.2558393	.828	-.420836	1.043754
3	0	-.0313721	.3634739	1.000	-1.071752	1.009008
	1	-1.3384435*	.2527556	.000	-2.061912	-.614975
	2	-1.2856190*	.2551124	.000	-2.015834	-.555405
	4	-.2991914	.2535247	.846	-1.024861	.426478
	5	-.9741603*	.2520023	.002	-1.695473	-.252848
4	0	.2678193	.3650401	.978	-.777044	1.312682
	1	-1.0392522*	.2550026	.001	-1.769152	-.309352
	2	-.9864276*	.2573389	.002	-1.723015	-.249840
	3	.2991914	.2535247	.846	-.426478	1.024861
	5	-.6749690	.2542560	.087	-1.402732	.052794
5	0	.9427882	.3639844	.102	-.099053	1.984630
	1	-.3642832	.2534892	.704	-1.089851	.361285
	2	-.3114587	.2558393	.828	-1.043754	.420836
	3	.9741603*	.2520023	.002	.252848	1.695473
	4	.6749690	.2542560	.087	-.052794	1.402732

*. The mean difference is significant at the 0.05 level.

One-way ANOVA: Molybdenum between bays

Mo
Tukey HSD

(I) Bay	(J) Bay	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
0	1	.0000556	.0016609	1.000	-.004698	.004809
	2	.0000988	.0016683	1.000	-.004677	.004874
	3	.0001757	.0016562	1.000	-.004565	.004916
	4	-.0018260	.0016633	.882	-.006587	.002935
	5	.0001634	.0016585	1.000	-.004584	.004911
1	0	-.0000556	.0016609	1.000	-.004809	.004698
	2	.0000432	.0011691	1.000	-.003303	.003390
	3	.0001202	.0011517	1.000	-.003176	.003417
	4	-.0018815	.0011619	.586	-.005207	.001444
	5	.0001078	.0011550	1.000	-.003198	.003414
2	0	-.0000988	.0016683	1.000	-.004874	.004677
	1	-.0000432	.0011691	1.000	-.003390	.003303
	3	.0000769	.0011624	1.000	-.003250	.003404
	4	-.0019247	.0011726	.571	-.005281	.001432
	5	.0000646	.0011657	1.000	-.003272	.003401
3	0	-.0001757	.0016562	1.000	-.004916	.004565
	1	-.0001202	.0011517	1.000	-.003417	.003176
	2	-.0000769	.0011624	1.000	-.003404	.003250
	4	-.0020017	.0011552	.511	-.005308	.001305
	5	-.0000123	.0011482	1.000	-.003299	.003274
4	0	.0018260	.0016633	.882	-.002935	.006587
	1	.0018815	.0011619	.586	-.001444	.005207
	2	.0019247	.0011726	.571	-.001432	.005281
	3	.0020017	.0011552	.511	-.001305	.005308
	5	.0019894	.0011585	.521	-.001327	.005305
5	0	-.0001634	.0016585	1.000	-.004911	.004584
	1	-.0001078	.0011550	1.000	-.003414	.003198
	2	-.0000646	.0011657	1.000	-.003401	.003272
	3	.0000123	.0011482	1.000	-.003274	.003299
	4	-.0019894	.0011585	.521	-.005305	.001327

One-way ANOVA: Phosphorus between bays

P
Tukey HSD

(I) Bay	(J) Bay	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	Upper Bound
0	1	-.1470013	.1531222	.930	-.585287	.291284
	2	-.0899630	.1538104	.992	-.530218	.350292
	3	.0435599	.1526885	1.000	-.393484	.480604
	4	-.3187921	.1533464	.300	-.757719	.120135
	5	-.2676998	.1529029	.499	-.705358	.169958
1	0	.1470013	.1531222	.930	-.291284	.585287
	2	.0570384	.1077849	.995	-.251477	.365554
	3	.1905612	.1061778	.470	-.113354	.494476
	4	-.1717907	.1071218	.597	-.478408	.134826
	5	-.1206985	.1064860	.867	-.425496	.184099
2	0	.0899630	.1538104	.992	-.350292	.530218
	1	-.0570384	.1077849	.995	-.365554	.251477
	3	.1335228	.1071679	.814	-.173226	.440272
	4	-.2288291	.1081032	.280	-.538255	.080597
	5	-.1777368	.1074732	.563	-.485360	.129886
3	0	-.0435599	.1526885	1.000	-.480604	.393484
	1	-.1905612	.1061778	.470	-.494476	.113354
	2	-.1335228	.1071679	.814	-.440272	.173226
	4	-.3623519*	.1065009	.009	-.667192	-.057512
	5	-.3112596*	.1058614	.040	-.614269	-.008250
4	0	.3187921	.1533464	.300	-.120135	.757719
	1	.1717907	.1071218	.597	-.134826	.478408
	2	.2288291	.1081032	.280	-.080597	.538255
	3	.3623519*	.1065009	.009	.057512	.667192
	5	.0510923	.1068081	.997	-.254627	.356812
5	0	.2676998	.1529029	.499	-.169958	.705358
	1	.1206985	.1064860	.867	-.184099	.425496
	2	.1777368	.1074732	.563	-.129886	.485360
	3	.3112596*	.1058614	.040	.008250	.614269
	4	-.0510923	.1068081	.997	-.356812	.254627

*. The mean difference is significant at the 0.05 level.

One-way ANOVA: Lead between bays

Pb
Tukey HSD

(I) Bay	(J) Bay	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
0	1	-.0354868	.0135133	.093	-.074166	.003193
	2	-.0130864	.0135740	.929	-.051940	.025767
	3	.0094556	.0134750	.982	-.029114	.048026
	4	-.0083244	.0135331	.990	-.047061	.030412
	5	-.0386218	.0134940	.050	-.077246	.000002
1	0	.0354868	.0135133	.093	-.003193	.074166
	2	.0224004	.0095122	.175	-.004827	.049627
	3	.0449424*	.0093704	.000	.018121	.071763
	4	.0271624*	.0094537	.049	.000103	.054222
	5	-.0031350	.0093976	.999	-.030034	.023764
2	0	.0130864	.0135740	.929	-.025767	.051940
	1	-.0224004	.0095122	.175	-.049627	.004827
	3	.0225421	.0094578	.164	-.004529	.049613
	4	.0047620	.0095403	.996	-.022545	.032069
	5	-.0255354	.0094847	.079	-.052684	.001613
3	0	-.0094556	.0134750	.982	-.048026	.029114
	1	-.0449424*	.0093704	.000	-.071763	-.018121
	2	-.0225421	.0094578	.164	-.049613	.004529
	4	-.0177801	.0093989	.409	-.044683	.009123
	5	-.0480774*	.0093425	.000	-.074819	-.021336
4	0	.0083244	.0135331	.990	-.030412	.047061
	1	-.0271624*	.0094537	.049	-.054222	-.000103
	2	-.0047620	.0095403	.996	-.032069	.022545
	3	.0177801	.0093989	.409	-.009123	.044683
	5	-.0302974*	.0094260	.018	-.057278	-.003317
5	0	.0386218	.0134940	.050	-.000002	.077246
	1	.0031350	.0093976	.999	-.023764	.030034
	2	.0255354	.0094847	.079	-.001613	.052684
	3	.0480774*	.0093425	.000	.021336	.074819
	4	.0302974*	.0094260	.018	.003317	.057278

*. The mean difference is significant at the 0.05 level.

One-way ANOVA: Zinc between bays

Zn
Tukey HSD

(I) Bay	(J) Bay	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	Upper Bound
0	1	-.0760847	.1076465	.981	-.384204	.232034
	2	-.0349136	.1081303	1.000	-.344417	.274590
	3	.0268157	.1073416	1.000	-.280431	.334062
	4	.0107260	.1078041	1.000	-.297844	.319296
	5	-.2190527	.1074923	.323	-.526731	.088625
1	0	.0760847	.1076465	.981	-.232034	.384204
	2	.0411711	.0757739	.994	-.175718	.258061
	3	.1029003	.0746441	.740	-.110755	.316556
	4	.0868107	.0753077	.859	-.128744	.302366
	5	-.1429681	.0748607	.397	-.357244	.071308
2	0	.0349136	.1081303	1.000	-.274590	.344417
	1	-.0411711	.0757739	.994	-.258061	.175718
	3	.0617293	.0753401	.964	-.153919	.277377
	4	.0456396	.0759976	.991	-.171890	.263169
	5	-.1841391	.0755548	.146	-.400401	.032123
3	0	-.0268157	.1073416	1.000	-.334062	.280431
	1	-.1029003	.0746441	.740	-.316556	.110755
	2	-.0617293	.0753401	.964	-.277377	.153919
	4	-.0160897	.0748712	1.000	-.230395	.198216
	5	-.2458684*	.0744216	.013	-.458887	-.032850
4	0	-.0107260	.1078041	1.000	-.319296	.297844
	1	-.0868107	.0753077	.859	-.302366	.128744
	2	-.0456396	.0759976	.991	-.263169	.171890
	3	.0160897	.0748712	1.000	-.198216	.230395
	5	-.2297787*	.0750872	.028	-.444703	-.014855
5	0	.2190527	.1074923	.323	-.088625	.526731
	1	.1429681	.0748607	.397	-.071308	.357244
	2	.1841391	.0755548	.146	-.032123	.400401
	3	.2458684*	.0744216	.013	.032850	.458887
	4	.2297787*	.0750872	.028	.014855	.444703

*. The mean difference is significant at the 0.05 level.

Tukey Multiple Post-Hoc Comparison of Elements across the VPS

Al

Bay	N	Subset for alpha = 0.05	
		1	2
3	86	37.27	
4	83	37.46	
Control	27	38.49	38.49
5	85	38.88	38.88
2	81		41.96
1	84		42.34
Sig.		0.88	0.09

Ca

Bay	N	Subset for alpha = 0.05	
		1	2
3	86	20.45	
4	83	21.77	
1	84	22.81	
2	81	23.21	
Control	27	23.92	23.92
5	85		27.21
Sig.		0.06	0.09

Cr

Bay	N	Subset for alpha = 0.05			
		1	2	3	4
2	81	0.14			
Control	27	0.15	0.15		
3	86	0.16	0.16	0.16	
1	84		0.16	0.16	
4	83			0.17	0.17
5	85				0.19
Sig.		0.105	0.31	0.49	0.32

Cu

Bay	N	Subset for alpha = 0.05	
		1	2
3	86	0.35	
Control	27	0.36	0.36
2	81	0.37	0.37
4	83	0.38	0.37
1	84	0.38	0.38
5	85		0.39
Sig.		0.19	0.21

K

Bay	N	Subset for alpha = 0.05	
		1	2
4	83	3.45	
5	85	3.59	
3	86	3.64	
Control	27	4.02	4.02
1	84		4.37
2	81		4.51
Sig.		0.11	0.22

Tukey Multiple Post-Hoc Comparison of Elements across the VPS (continued)

Mg

Bay	N	Subset for alpha = 0.05		
		1	2	3
3	86	9.15		
Control	27	9.18		
4	83	9.45	9.45	
5	85		10.12	10.12
2	81			10.44
1	84			10.49
Sig.		0.91	0.20	0.82

Mo

Bay	N	Subset for alpha = 0.05
		1
3	86	0.000047
5	85	0.000059
2	81	0.000123
1	84	0.000167
Control	27	0.000222
4	83	0.002048
Sig.		0.67

P

Bay	N	Subset for alpha = 0.05	
		1	2
3	86	5.00	
Control	27	5.05	5.05
2	81	5.14	5.14
1	84	5.19	5.19
5	85	5.31	5.31
4	83		5.37
Sig.		0.13	0.11

Pb

Bay	N	Subset for alpha = 0.05	
		1	2
3	86	0.42	
Control	27	0.423	
4	83	0.44	0.44
2	81	0.44	0.44
1	84		0.46
5	85		0.47
Sig.		0.31	0.07

Zn

Bay	N	Subset for alpha = 0.05
		1
3	86	0.83
4	83	0.84
Control	27	0.86
2	81	0.89
1	84	0.93
5	85	1.07
Sig.		0.06

Means for groups in homogeneous subsets are displayed.
a. Uses Harmonic Mean Sample Size = 62.029.
b. The group sizes are unequal.
The harmonic mean of the group sizes is used.
Type I error levels are not guaranteed.

C. Boxplots of Mean Element Concentrations across the VPS.

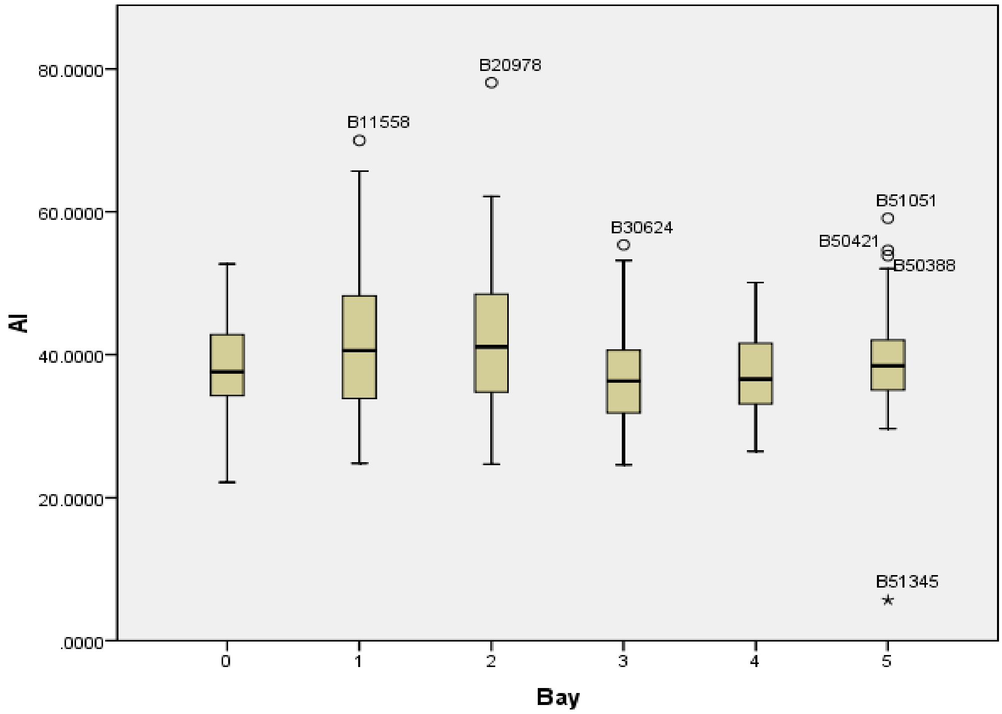


Figure 1 Boxplot displaying Aluminium concentrations (mg kg^{-1}) from samples taken from the VPS

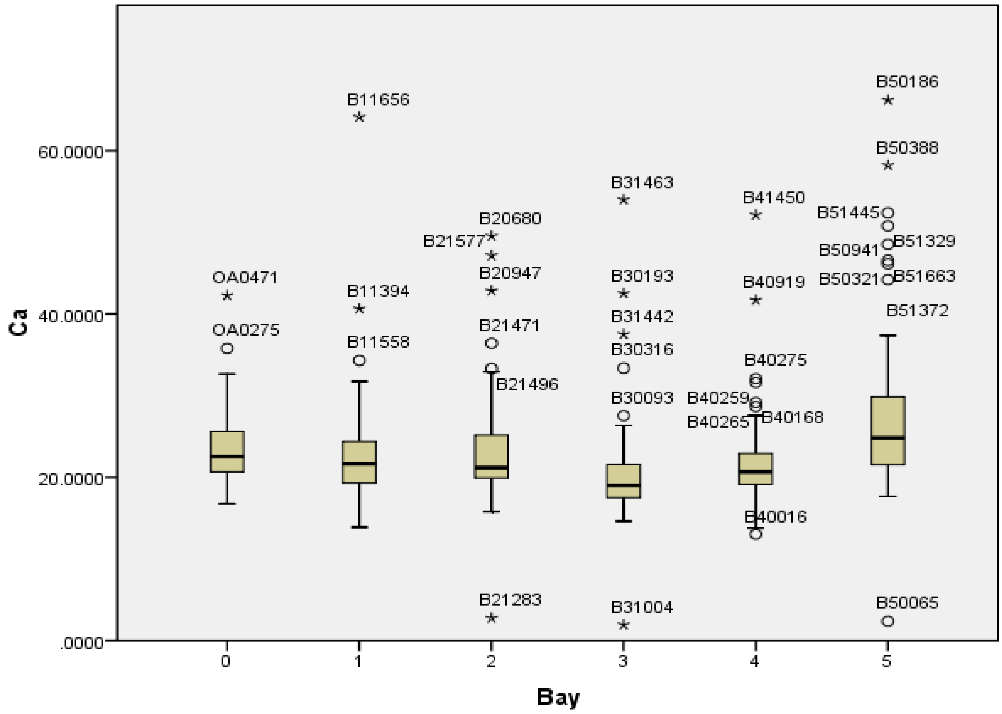


Figure 2 Boxplot displaying Calcium concentrations (mg kg^{-1}) from samples taken from the VPS

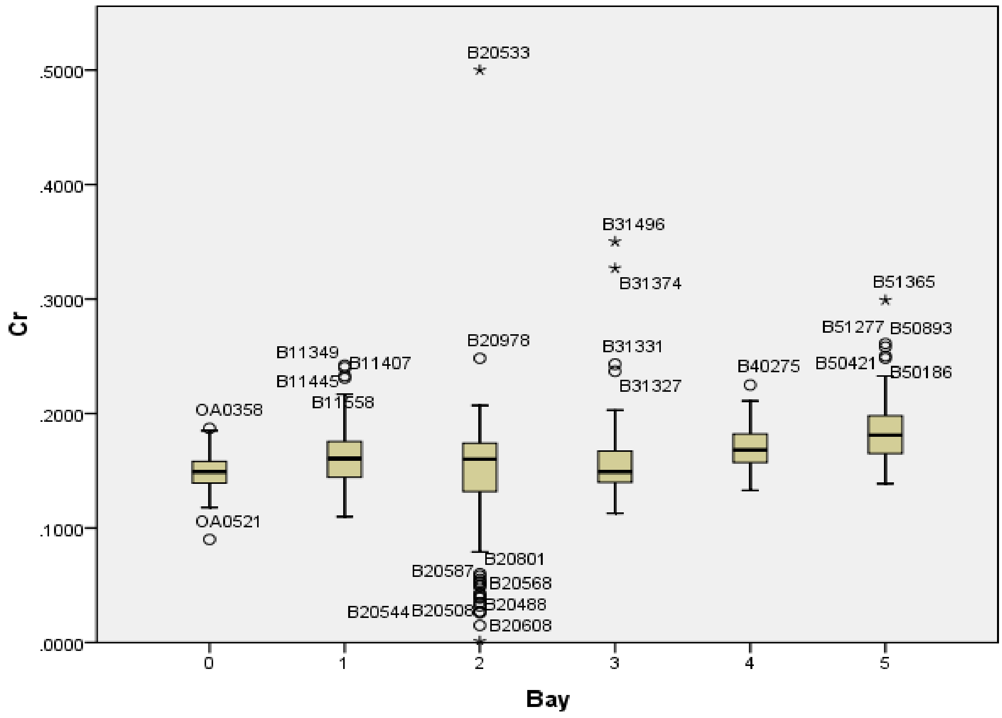


Figure 3 Chromium concentrations (mg kg^{-1}) from samples taken from the VPS

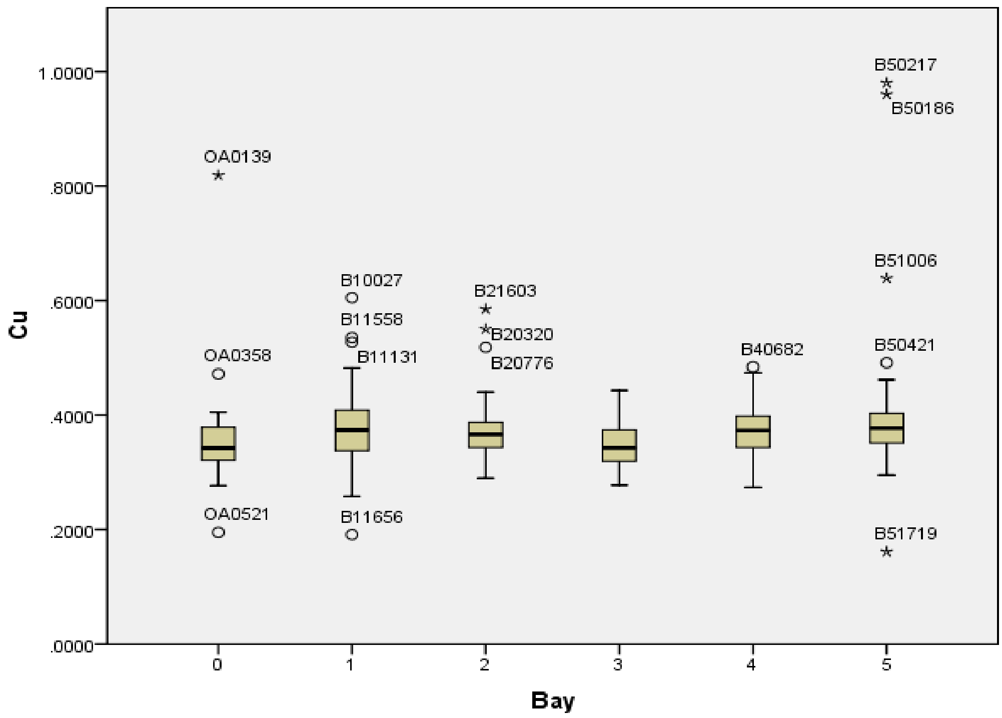


Figure 4 Boxplot displaying Copper concentrations (mg kg^{-1}) from samples taken from the VPS

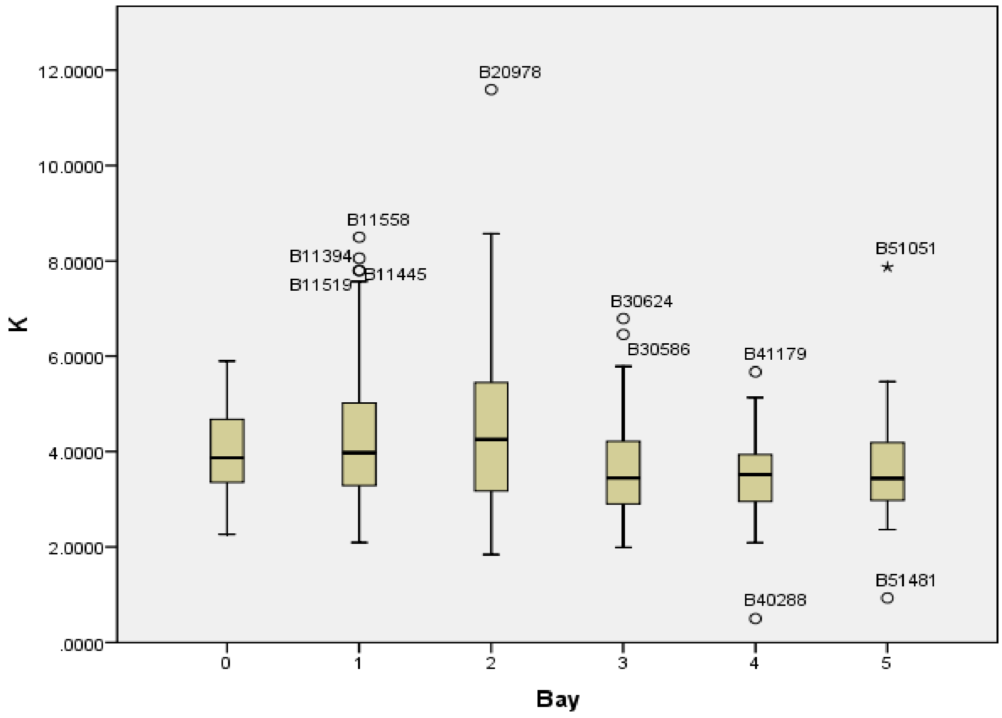


Figure 5 Boxplot displaying Potassium concentrations (mg kg^{-1}) from samples taken from the VPS

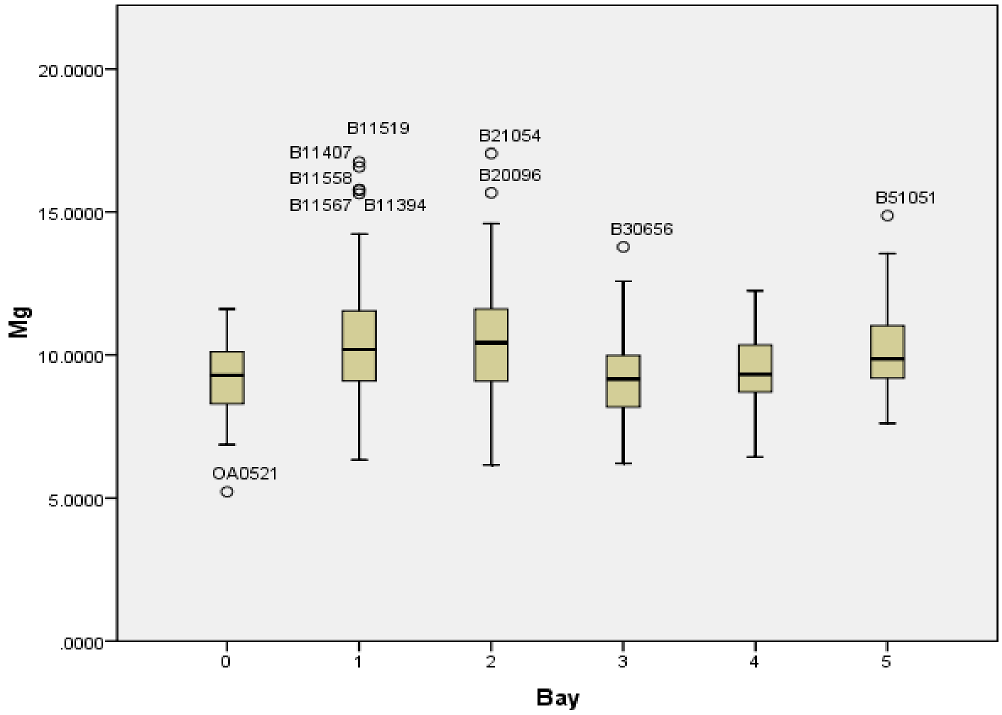


Figure 6 Boxplot displaying Magnesium concentrations (mg kg^{-1}) from samples taken from the VPS

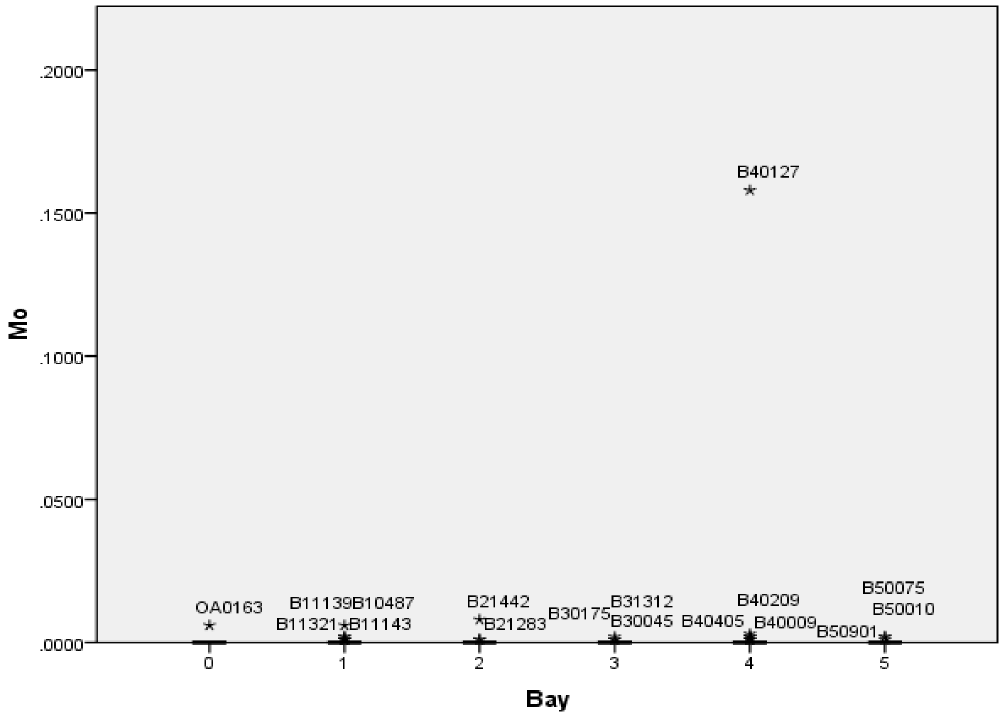


Figure 7 Boxplot displaying Molybdenum concentrations (mg kg^{-1}) from samples taken from the VPS

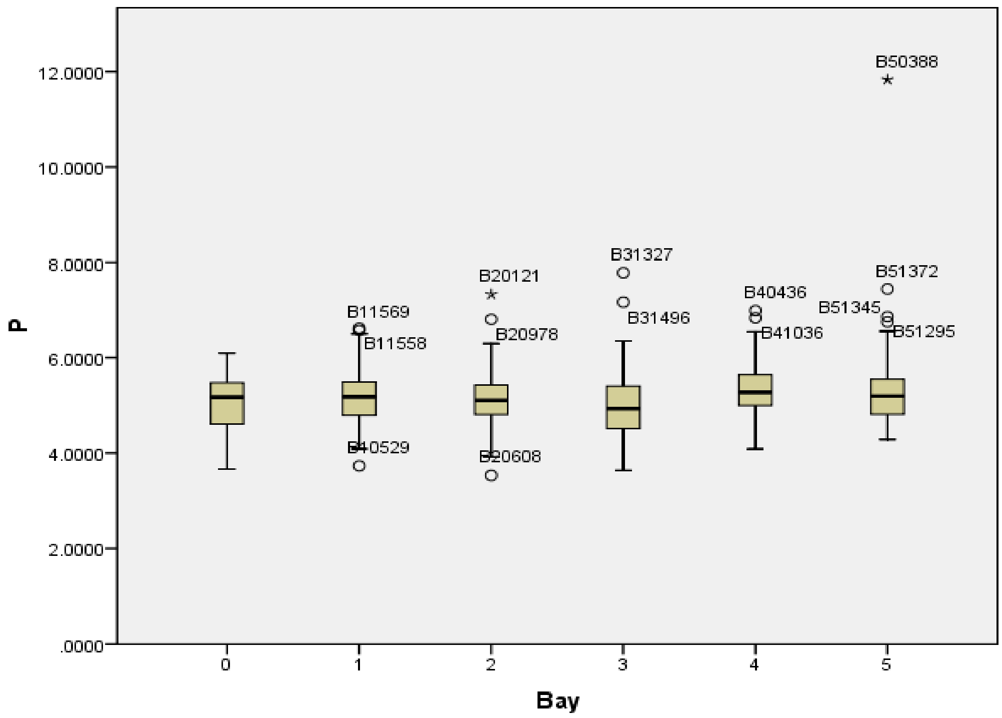


Figure 8 Boxplot displaying Phosphorus concentrations (mg kg^{-1}) from samples taken from the VPS

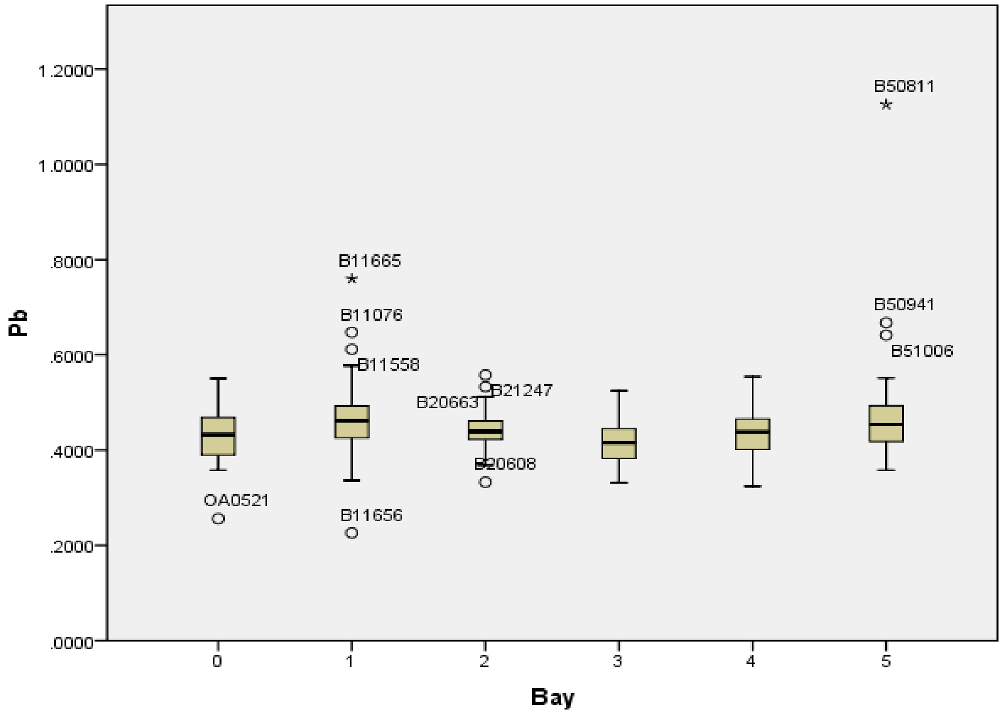


Figure 9 Boxplot displaying Lead concentrations (mg kg^{-1}) from samples taken from the VPS

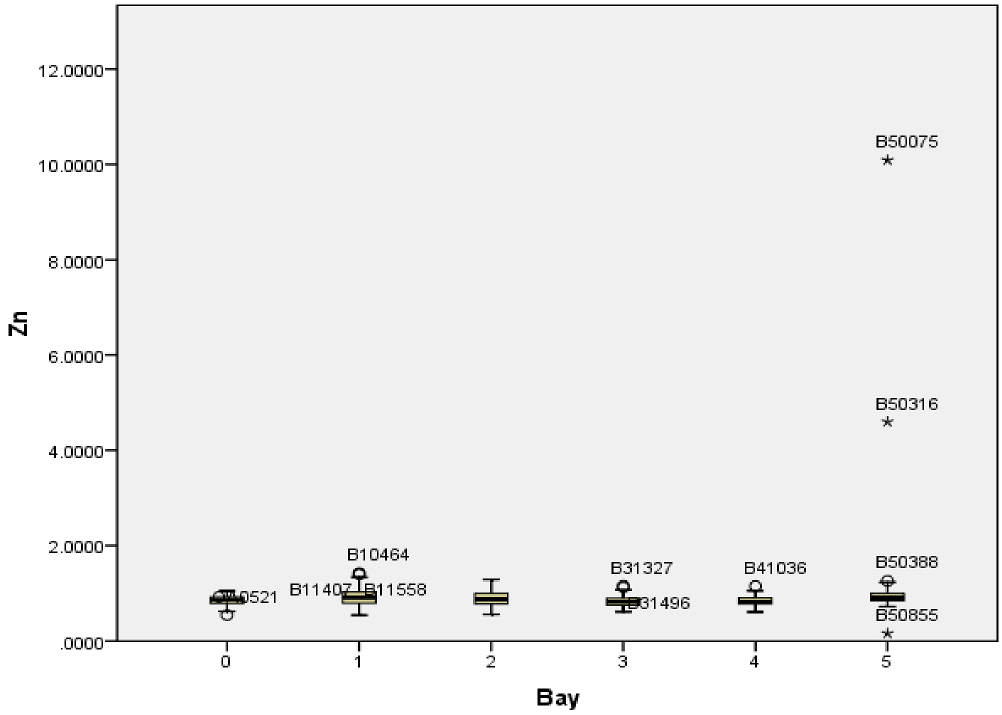


Figure 10 Boxplot displaying Zinc concentrations (mg kg^{-1}) from samples taken from the VPS

D. Survey of VPS Usage by School Staff

Questionnaire Consent Form

Clinton Primary School Staff and Visitors Car Park
Questionnaire on Car Park Use

Principal Investigator
Miss Michelle Barrett.
Ph.D Student, Dept. of Geography, Environment and Disaster Management, Faculty of Business, Environment and Society, Coventry University.

Director of Studies for the Principal Investigator
Dr. Susanne Charlesworth
Senior Lecturer, Dept. of Geography, Environment and Disaster Management, Faculty of Business, Environment and Society, Coventry University.

Project Purpose and Procedures

This research project is designed to investigate the parking habits of car users on their arrival at Clinton Primary School, Kenilworth. This questionnaire aims to determine how often the grass surface parking bay are parked on and if there are specific reasons for grass-surfaced bay usage.

The purpose of this research project is to gather information that indicates the amount of usage of the current grass surface parking bays, on a regular basis. You are being asked to complete a questionnaire to assist the investigation in that regard. It is expected that it will take no more than 15 minutes to complete the questionnaire. There are no risks or situations that will cause harm to you, in relation to this questionnaire.

Although only a research project in its current form, this project may, at a later date, be extended by the principal investigator.

Confidentiality

The identities of all people who participate will remain anonymous and will be kept confidential. Identifiable data is not required for this questionnaire; however, all replies will be stored securely in a locked metal filing on their return to the principal investigator. All data from individual participants will be coded so that their anonymity will be protected in any reports, research papers, thesis documents, and presentations that result from this work.

Remuneration/Compensation

I am extremely grateful for your participation. A gift will be offered to the staff on completion and return of the questionnaires. A copy of the completed Ph.D thesis will be given to the school, following the completion of the research.

Contact Information about the Project

If you have any questions or require further information about the project, you may contact the principal investigator, Michelle Barrett on 02476 887626 or mbarrett@coventry.ac.uk.

Contact for information about the rights of research subjects

If you have any concerns about your treatment or rights as a research subject, you may contact the Coventry University Ethics Committee:

Ray Carson, Chair (Ray.Carson@coventry.ac.uk) - 024 7688 8613
David Ellard, Vice-Chair (D.Ellard@coventry.ac.uk) - 024 7688 7458
Rhoda Morgan, Administrator (R.Morgan@coventry.ac.uk) - 024 7679 5945

I intend for your participation in this project to be pleasant and stress-free. Your participation is entirely voluntary and you may refuse to participate or withdraw from the study at any time.

Consent

I have read and understood the above information, have had any questions answered satisfactorily, and I willingly consent to participate in this study.

I understand that if I should have any questions about my rights as a research subject, I can contact the members of the Coventry University Ethics Committee, as mentioned above.

I can also contact the Director of Studies of the principal investigator, Dr. Susanne Charlesworth by email: s.charlesworth@coventry.ac.uk or by phone at 024 7688 8370.

I have received a copy of this consent form.

Signed: ……………………………………………………………………………..

Date: ……………………………………………………………………………….

Clinton Primary School Staff and Visitors Car Park
Questionnaire on Car Park Use

1. Do you park…?

    a. On the tarmac parking bays (go to Qu. 2)
    b. On the grass surface parking bays (go to Qu. 3)
    c. On both the tarmac and the grass parking bays (go to Qu. 3)
    d. Elsewhere, please state (go to Qu. 2)
    ……
    ……………………………

2. Why do you park on the tarmac surface parking bays or elsewhere, and not on the grass surface parking bays?

    a. Didn't know the grass surface bays existed
    b. Out of habit
    c. Find it difficult to drive or reverse into the grass surface parking bays
    d. There are always tarmac parking bays available when I need them
    e. A parking place is guaranteed elsewhere
    f. Other, please state
    ……
    ……………………………

    (go to Qu. 7)

3. How often do you park on the grass surface parking bays?

    a. Once a week (go to Qu. 4)
    b. Twice a week (go to Qu. 4)
    c. Three times a week (go to Qu. 4)
    d. Four times a week (go to Qu. 4)
    e. Each day (go to Qu. 4)
    f. Only when there's no tarmac spaces available (go to Qu. 6)

Bay 1 Nearest school gate	Bay 2	Bay 3	Bay 4	Bay 5 Nearest path to school reception

Figure 1. Schematic diagram of the grass surface parking bays

4. If the grass surface parking bays were numbered as Figure 1 (above), which bay do you park in most often?

    a. Bay 1
    b. Bay 2
    c. Bay 3
    d. Bay 4
    e. Bay 5

    (go to Qu. 5)

5. Do you…?
    a. Drive into the bay forwards
    b. Reverse into the bay
    c. Drive on to the bay at an angle

    (go to Qu. 6)

6. Why do you prefer this particular bay?

    a. Nearest to the entrance of the school building
    b. Easiest to drive forwards into
    c. Easiest to reverse into
    d. The bay that has more grass cover so my footwear doesn't get too muddy
    e. It's usually available when I need it
    f. Other, please state
    ……
    ……………………………

(go to Qu. 7)

7. Which bay would you be most likely to use if there were no tarmac spaces available and all the grass spaces were available? (please refer to the schematic diagram in Figure 1).

    a. Bay 1
    b. Bay 2
    c. Bay 3
    d. Bay 4
    e. Bay 5

(go to Qu. 8)

8. When do you favour grass surface parking bays over the tarmac surface parking bays?

    a. When there are no tarmac surface bays available
    b. When I am in a rush
    c. When I am not in a rush
    d. When the weather is fine
    e. When the weather is bad
    f. When I have extra books or equipment to carry into the school
    g. Other, please state ………

(go to Qu.9)

9. If you generally park on the tarmac surface parking bays or elsewhere, would you consider parking on the grass surface parking bays in the future?

    a. Yes
    b. Maybe, if that is all that is left
    c. No, please state why ………

(go to Qu. 10)

10. When the grass bays are empty, do you walk across them as a short cut?

    a. Yes
    b. No
    c. Occasionally

    (go to Qu. 11)

11. Does bad/wet weather affect your decision to park on the grass surface parking bays?

    a. Yes (go to Qu. 12)
    b. No (go to Qu. 13)

12. How does this weather affect your decision? Please circle answer.

    a. Want to be nearer to school in bad weather Y N ?
    b. Shoes become stuck in the wet ground Y N ?
    c. If visibility is bad, prefer to drive into spaces that don't require too much manoeuvrability Y N ?
    d. More people park in tarmac areas in wet weather, grass spaces are all that's left Y N ?
    e. Other, please state ……

    (go to Qu. 13)

13. What is your opinion on the grass surface parking bays? (1 = agree strongly, 3 = neither agree nor disagree or no opinion, 5 = strongly disagree)

    a. They look more aesthetic than tarmac bays 1 2 3 4 5
    b. They help with the clean up of contaminants 1 2 3 4 5
    c. They help with drainage of rainfall 1 2 3 4 5
    d. They provide extra space 1 2 3 4 5
    e. They require too much maintenance 1 2 3 4 5
    f. They seem a complex option for a car park 1 2 3 4 5
    g. Installation in other car parks will help controlling the contamination of the environment 1 2 3 4 5

h. Other opinion, please state
……
……………………………

(go to Qu. 14)

Some general questions

14. Are you…?

    a. Male
    b. Female

    (go to Qu. 15)

15. How old are you?

    a. 17-19
    b. 20-29
    c. 30-39
    d. 40-49
    e. 50-59
    f. 60+

    (go to Qu. 16)

16. How long have you been driving?

    a. Less than a year
    b. One to five years
    c. Six to 10 years
    d. 11 to 15 years
    e. 16 years plus

    (go to Qu. 17)

17. Please state your car details

    a. Make ………
    b. Model. ………
    c. Year of first registration ………
    d. Last service ………
    e. Last MOT (if applicable) ………

    (go to Qu. 18)

18. Are there any questions in this questionnaire that were not fully understandable?
    a. Yes, please state ………
    b. No

    (go to Qu. 19)

19. Are there any questions I should have asked you with reference to the grass surface parking bays?
    a. Yes, please expand on what I should have asked ………
    b. No

    (go to Qu. 20)

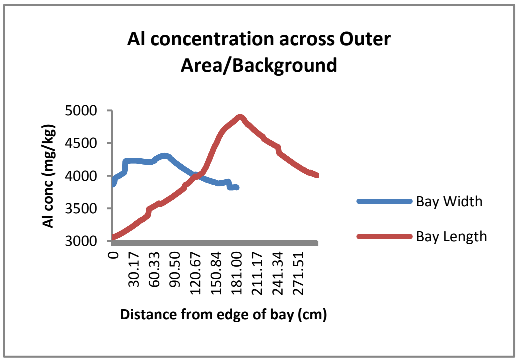
20. Any other comments on this questionnaire?

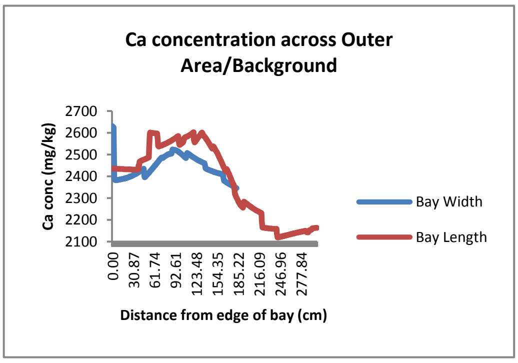
……
……
……
……
……
……
………………………………………………………………………………………………………

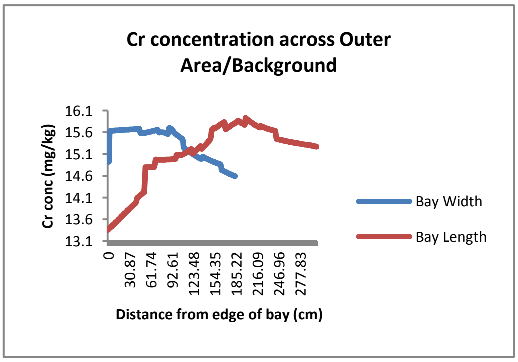
Many thanks.

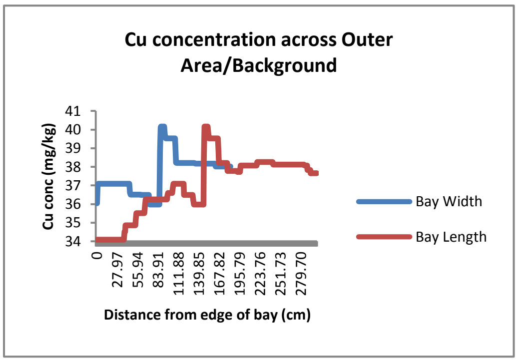
Michelle Barrett
Ph.D Research Student
Dept. of Geography, Environment and Disaster Management
Faculty of Business, Environment and Society
Coventry University

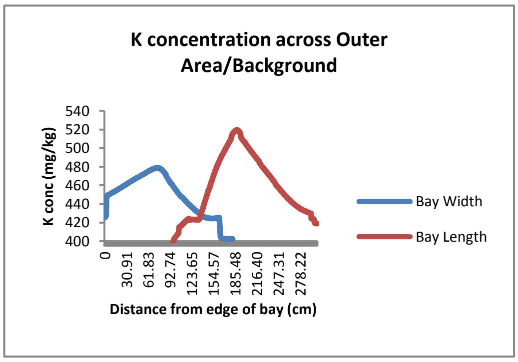
E. Profile Charts of Element Concentrations across the Background/Outer Area

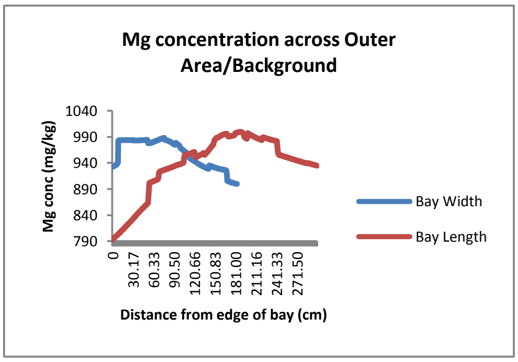


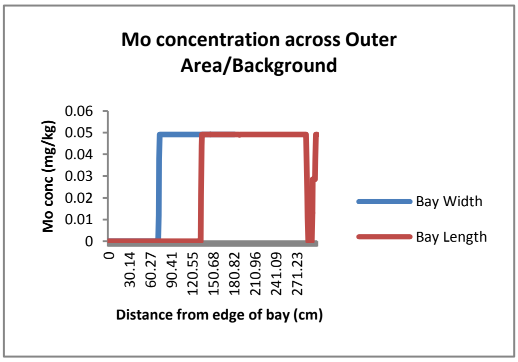


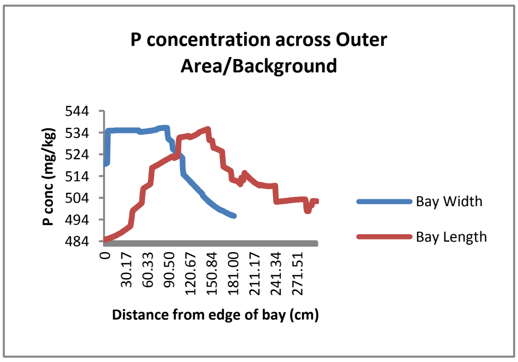


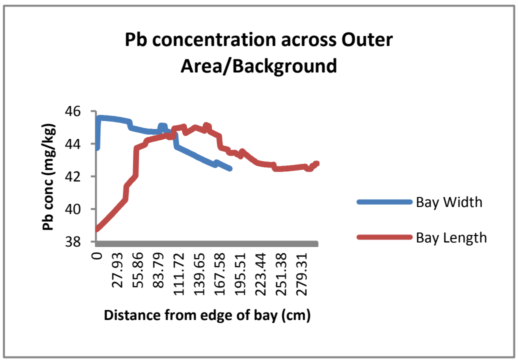


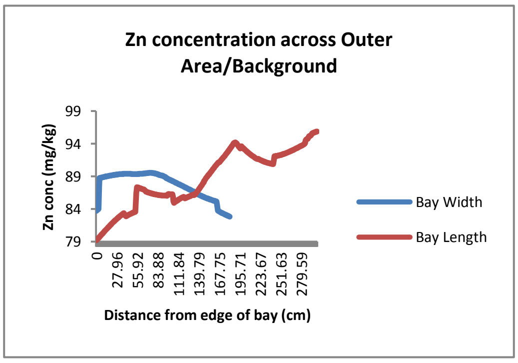




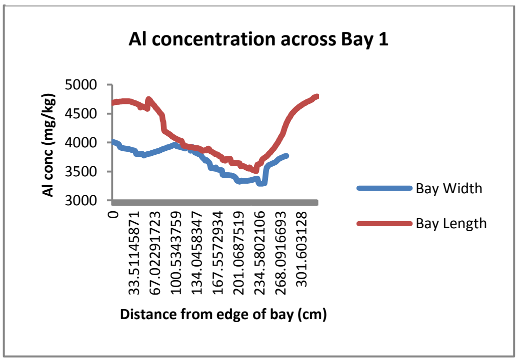


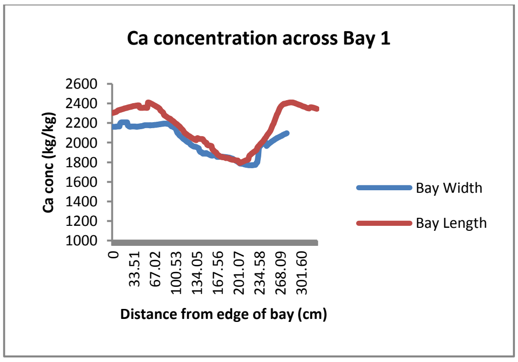


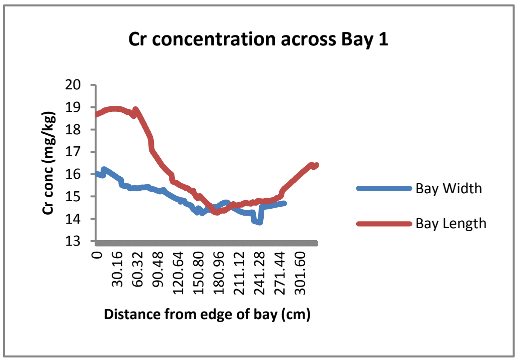


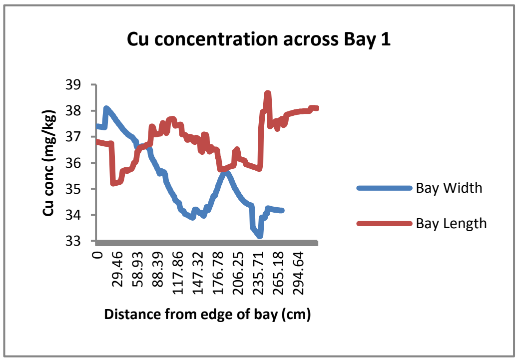


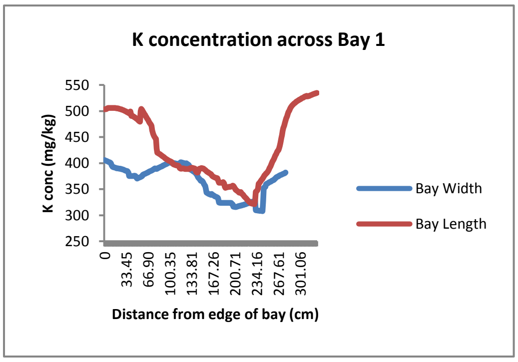
Profile Charts of Element Concentrations across Bay 1

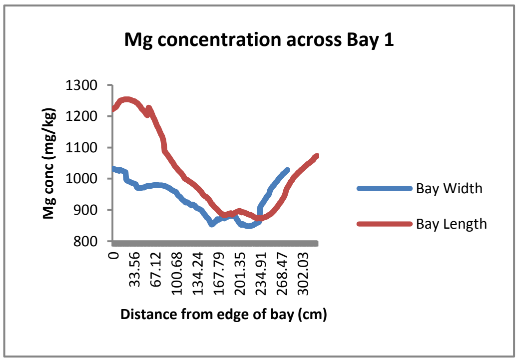


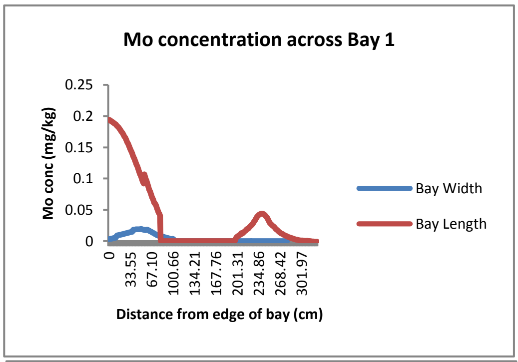


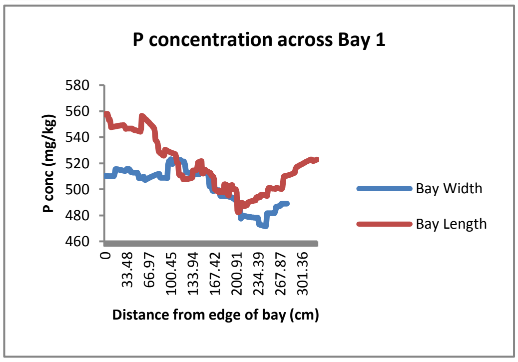


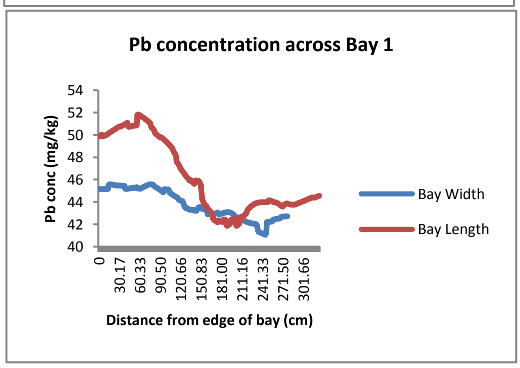


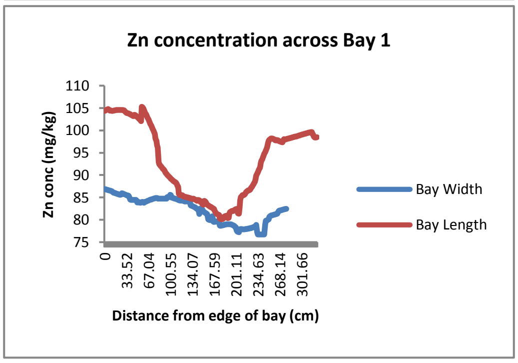




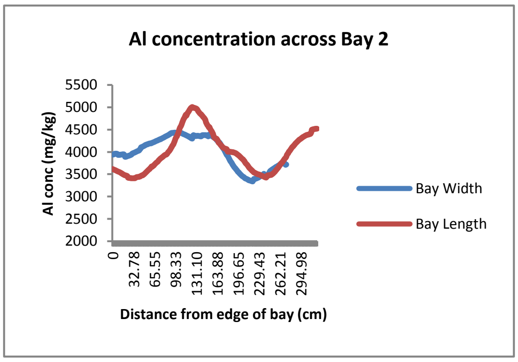


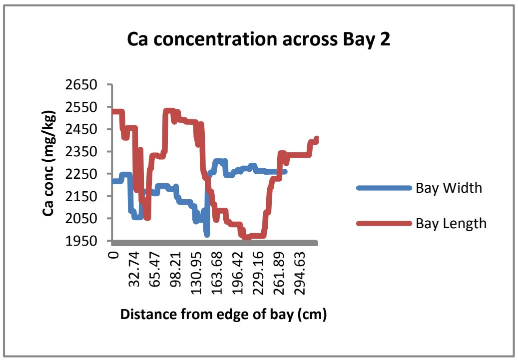


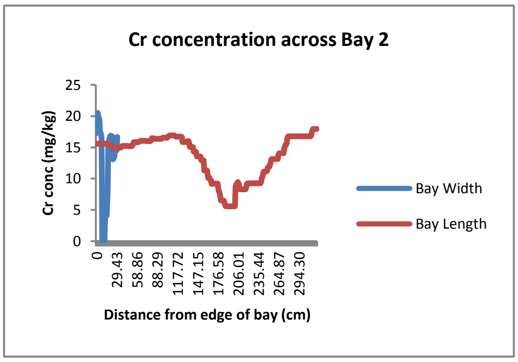


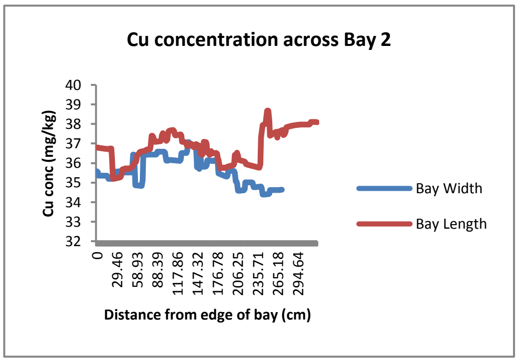


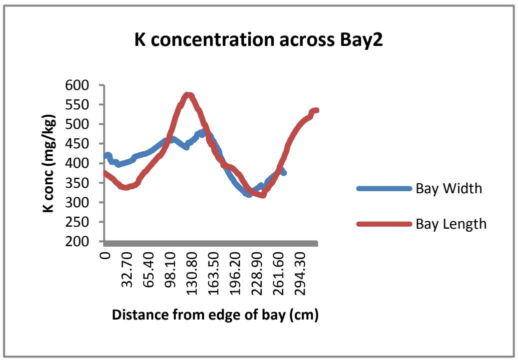
Profile Charts of Element Concentrations across Bay 2

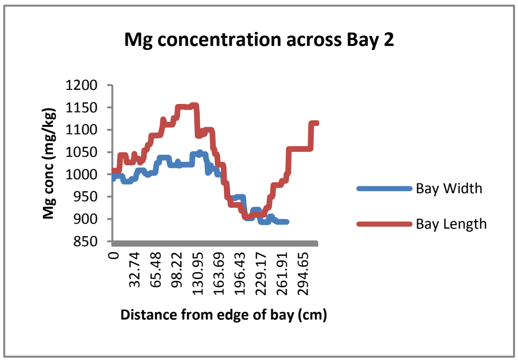


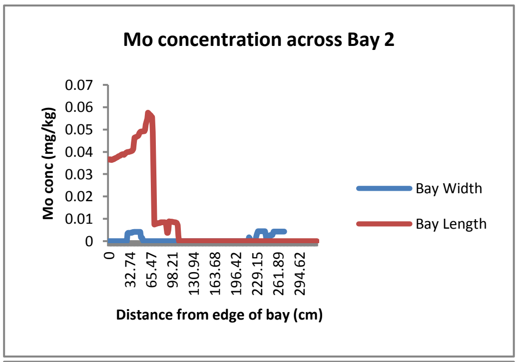


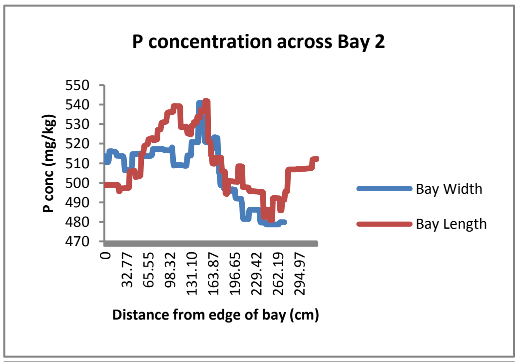


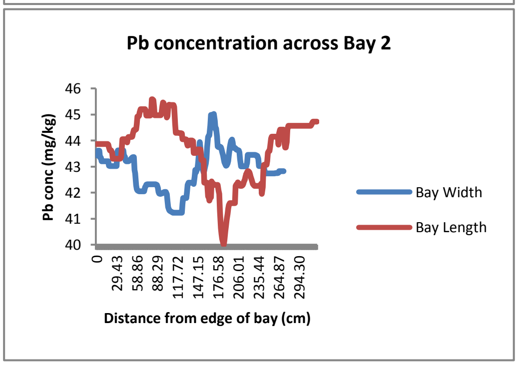


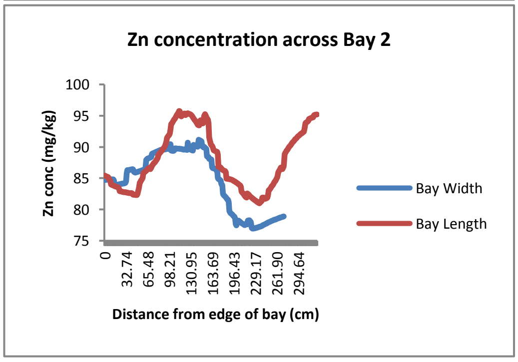




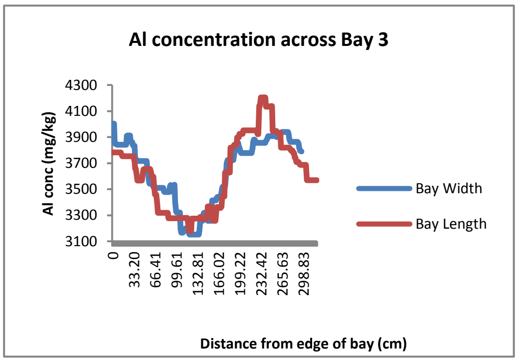


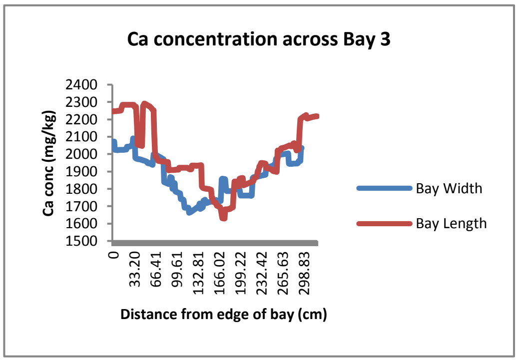


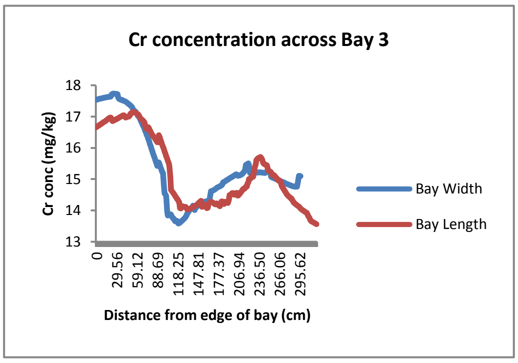


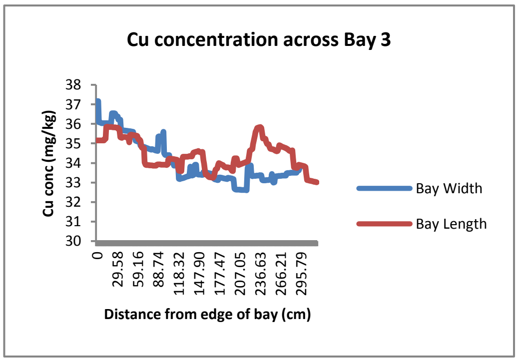


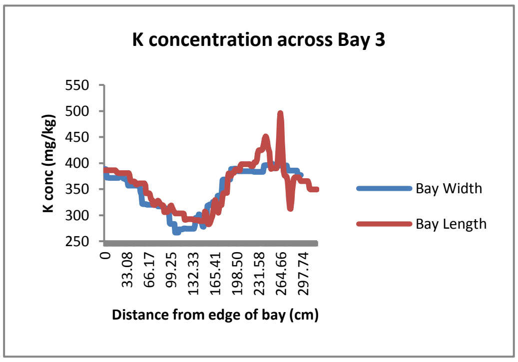
Profile Charts of Element Concentrations across Bay 3

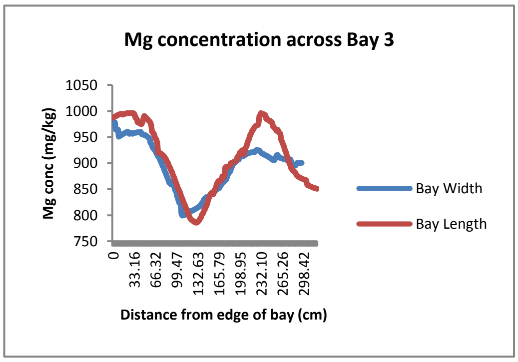


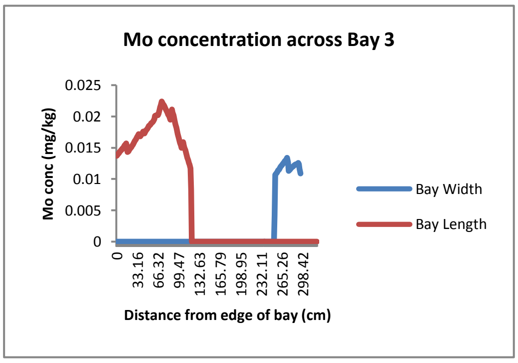


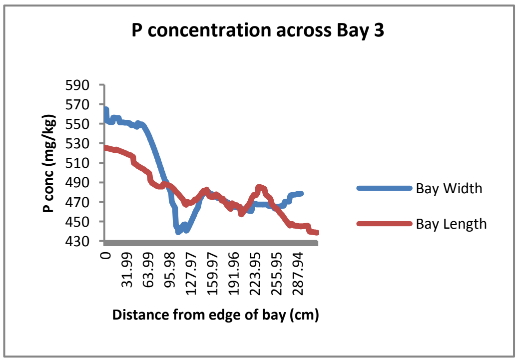


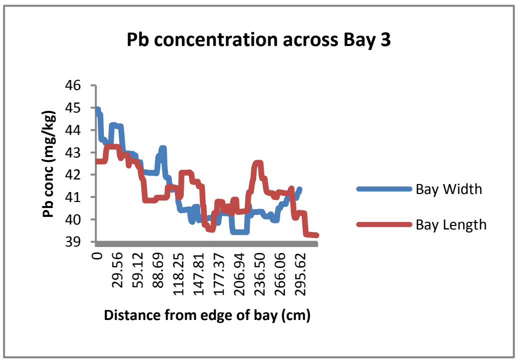


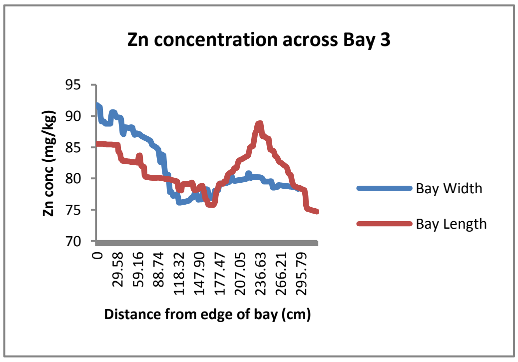




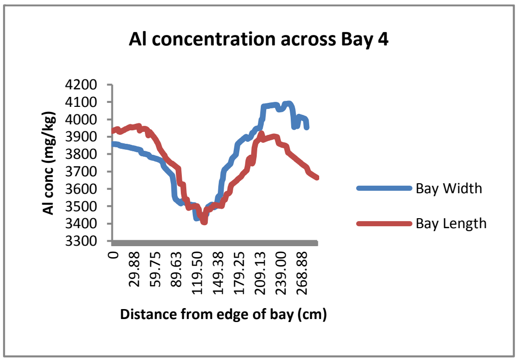


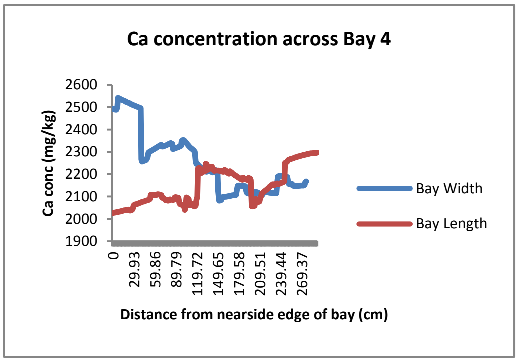


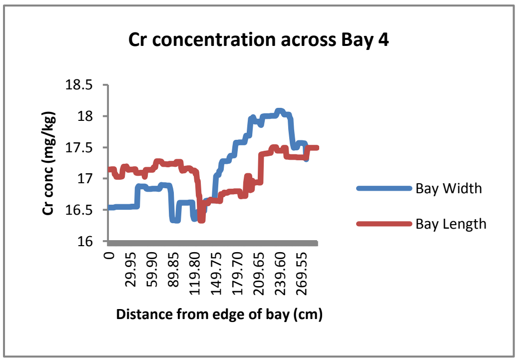


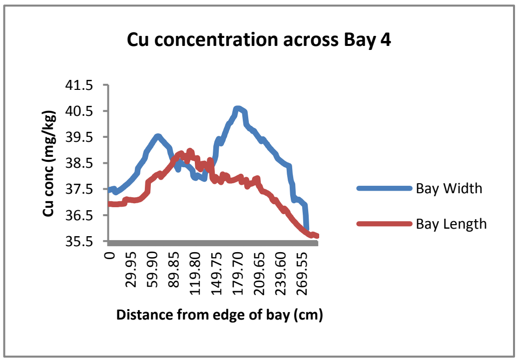


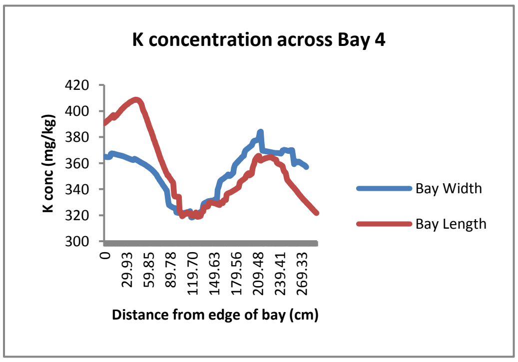
Profile Charts of Element Concentrations across Bay 4

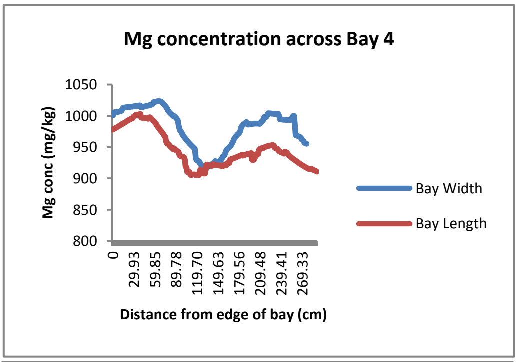


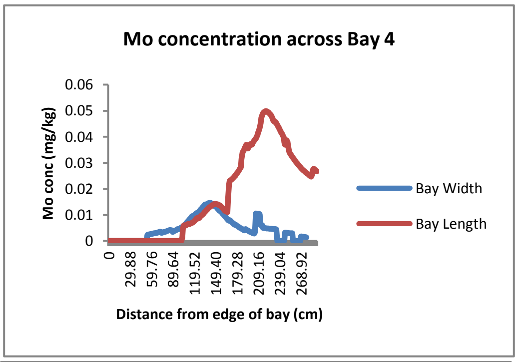


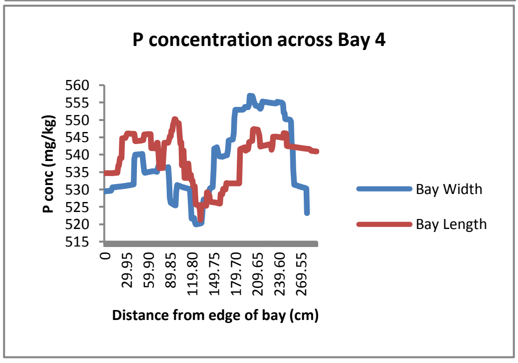


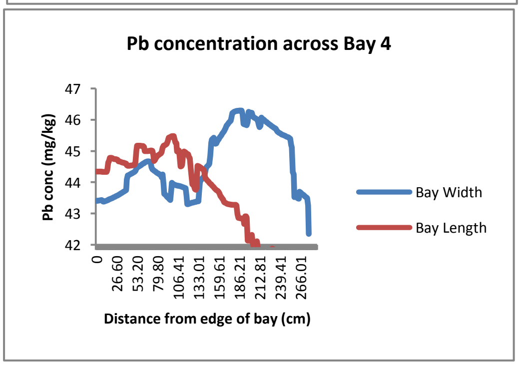


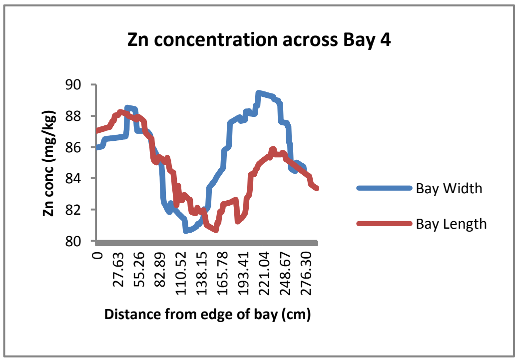












Profile Charts of Element Concentrations across Bay 5